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Empirical Essays on the Information Transfer Between and the Informational Efficiency of Stock Markets

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Proefschrift

ter verkrijging van de graad van doctor aan de Universiteit van Tilburg, op gezag van de rector magnificus, prof. dr. F.A. van der Duyn Schouten, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op woensdag 25 juni 2008 om 10.15 uur door

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"*Народу не нужны нездоровые сенсации. Народу нужны здоровые сенсации.*"

Аркадий и Борис Стругацкий. Сказка о тройке

To Rachel, Shaul and Galla with love

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Contents

Chapter 1

Introduction

Recent decades were marked by a rapid convergence of economies to a global market. Terms, such as "globalization", "integration" and "contagion" became an integrable part of both academics' and finance practitioners' as well as policy makers' everyday dictionary. The benefits and costs of globalization oriented policies became an issues of harsh political and social debates around the globe. One of the particularly important aspects is the impact of globalization on the links between the international stock markets. A drastic increase in the cross-border capital flows on the one hand and an increasing number of companies choosing to list their shares abroad on the other raises the question of whether the stock markets became more interdependent. The severe financial crises the world has witnessed over the last decade emphasized the importance of deeper understanding these links and the need of evaluating the impact of globalization on the propagation of financial crises around the world. However, many gaps still exist in the literature which concerns the impact of globalization on the comovement between the international stock markets. The first part of this thesis focuses on studying the dynamics of the cross-border transfer of pricing information between the international stock markets.

In Chapter 2 we study the interdependence structure between the major developed stock markets and how this structure has changed over the last two and a half decades. We make a distinction between long-run and short-run dynamics. A gradual shift in the dependence structure is potentially attributed to globalization oriented policies and can be viewed as evidence that the stock markets have become more integrated over time. On the other hand, temporary shifts in the dependence structure associated with stock market turbulence can serve as evidence of financial crises being "contagious". We make use of copula theory, which allows us to decompose a multivariate distribution function into its margins and the dependence function, or the copula. The dynamics of the latter becomes the focus of this chapter.

Our analysis indicates that the stock markets became significantly more integrated over the last two a half decades. Also, we find strong evidence of contagion. The "contagion effect" appears to be asymmetric, being significantly stronger for the negative pricing shocks and related to the stock market volatility and the economic conditions. These findings emphasize an important role of these factors in the international propagation of stock market crises. In particular, these results help us to understand the October 1987 phenomenon, when the crash of the US stock markets has rapidly propagated to the rest of the world. Economic costs of ignoring contagion or its asymmetric nature are significant as well. Also, by highlighting the importance of accounting for the shifts in the dependence structure between financial assets these results have an important implications for portfolio management strategies.

In Chapter 3 of this thesis we focus on the information transfer mechanism between the securities listed on both the New-York and Tokyo stock markets, the two largest and most influential stock markets in the world. By representing the same underlying fundamental value on the one hand and being traded on multiple trading locations on the other, cross-listed securities provide a unique framework for understanding the mechanism of the information transfer between the markets. In particular, they help us to understand the price discovery process in a world with financial systems becoming increasingly more integrated.

We find significant evidence of the information asymmetry with the Tokyo market emerging as the informationally dominant one where the lions share of the price discovery occurs. It takes more time for the pricing shocks from the Tokyo market to dissipate in the US market than vice versa, a finding, which suggests that the behavior of the US "twin" can be predicted based on the information released during the Tokyo trading session. This, in turn, implies that there exists a potential for designing profitable cross-border trading strategies. Moreover, the speed of the price-discovery appears to be related to the level of the trading activity, proxied by the trading volume. This result supports other studies, such as Blume, Easley, and O'Hara (1994), who suggest that trading volume provides extra information in addition to the one implicit in stock prices.

The second part of this thesis focuses on stock market efficiency, in particular on how fast the information is impounded in stock prices. The importance of understanding the mechanism of how the news is reflected in security prices can be hardly overestimated. It is essential for finance practitioners in their investment decisions, firms' management in their information disclosure policies as well as for policy makers whose decisions frequently have a great impact on the functioning of stock markets. All these aspects are examined in the following essays.

Chapter 4 studies the link between the predictable patterns of stock returns, trading volume, and volatility. We test a variety of theoretical models which link these variables to the dynamics of stock returns for a sample of both aggregate stock market indices and individual stocks. A combination of seminonparametric and parametric methodologies provides us a deeper insight into the nature of these relations and also contributes to the robustness of our findings. We find that the magnitude of the stock returns' reversals and "momentum" is mainly related to the stock market volatility and not to volume, whose impact appears to be of a secondary magnitude. This finding sheds a new light on the previously documented volume-return relation. However, the trading volume appears to play an important role in the price discovery process as well as in the comovement between stock prices, a finding, which highlights the importance of the informational content of the trading volume. Also, these findings provide an alternative explanation to the "high volume premium", documented by Gervais *et al.* (2001).

In Chapter 5 we examine the link between the information disclosure rules and market efficiency. We study the implications of the Sarbanes-Oxley Act of 2002, enacted as a response to a series of severe corporate scandals, for the market efficiency and the accuracy of the analysts' earnings forecasts. We examine whether the enactment of stricter disclosure requirements restored the confidence of the stock market investors and the analysts in the information disclosed by firms' management, which has been shaken by numerous cases of corporate fraud during the period 2001-2002.

Using a comprehensive sample of NYSE/AMEX listed firms we find that the enactment of the Sarbanes-Oxley Act has been followed by a substantial increase in the speed of adjustment coefficients. This finding suggests that following the reform the US stock markets became more informationally efficient. On the other hand, we find strong evidence of the analysts' becoming more "overpessimistic" in their earnings forecasts. We interpret this finding as the evidence of analysts becoming more cautious in interpreting the information released by the firms' management. Overall, these finding highlight a strong link between the quality of the information disclosure and the efficient functioning of stock markets.

Chapter 6 of this thesis is concerned with strategic timing of information disclosure and the response of stock prices to the news. We study the alleged tendency of firms to report more "bad" news close to the weekend, in particular on Fridays, using investors' distraction as the weekend approaches. However, if the investors learned about this strategy, we would expect its benefits to disappear over time. We find that over the last two decades the firms consistently released more "bad" news on Fridays than during other weekdays. We also document that the sensitivity of stock returns to Friday announcements compared to other weekdays has gradually increased over time, an increase which is particularly pronounced when the "bad" news is released. Furthermore, we document a strong link between the magnitude of the "Friday effect" and the level of the pre-announcement uncertainty. These findings suggest that the tendency of firms to release unfavorable announcements on Fridays is indeed related to the investors' distraction as the weekend approaches and that the benefits from using this strategy seem to dissipate over time, a result, which also yields important implications for the firms' announcement policies.

Finally, in Chapter 7 we summarize our findings and present concluding remarks in Dutch (Samenvatting).

Chapter 2

On the dependence structure, integration and contagion of the international stock markets

2.1 Introduction

Understanding the nature and the dynamics of the cross-border transmission of pricing information is important, not only for academics in various fields of economics and finance, but also for practitioners and policy regulators. Identifying and measuring the relative importance of global pricing factors, investigating whether globalization oriented policies lead to an increase in intermarket integration, choosing an optimal portfolio −these are only a few of examples where a proper understanding of the international stock markets' dependence structure plays a crucial role. As consequence, modeling the comovements between the international stock markets is an important task in empirical finance.

Among various aspects of stock market comovement, the question whether stock markets became more integrated and whether pricing shocks are contagious, gained special attention in the recent literature. An increasing economic integration, followed by a removal of impediments to international investments, naturally raises the question whether such policy steps resulted in a greater interdependence between the stock markets, and, if so, it raises the subsequent question of the implications for international portfolio diversification strategies. For instance, in terms of a traditional correlation analysis, an increase in cross-market correlations, might substantially reduce the benefits from investing in assets traded on different markets, possibly resulting in a shift from cross-country to, for example, cross-industry diversification strategies.

In contrast to an increase in market integration, which can be viewed as a long-run shift in the dependence structure, the contagion phenomenon is most often attributed to short-run dynamics of stock markets comovements. Among various definitions of what contagion really means, numerous studies concentrate on the definition proposed by Rigobon (1999), who defines stock market contagion as a shift (in general, an increase) in the interdependence of the stock markets during a crisis, in particular, there is contagion when stock markets move more closely together during turbulent periods. The crash of October 1987, the Latin American "Tequila crisis" of 1994, the "Asian Flu" in 1997, the devaluation of the Russian debt in 1998 −all these episodes manifest one common characteristic: a rapid propagation of pricing shocks across the stock markets whose magnitude can hardly be explained by any standard theory based on underlying fundamental values. These worldwide defaults raise the question whether the very fact of a financial crisis in one market increases the probability of its transmission to other markets, or, in other words, whether financial crises are "contagious", and, if so, the question becomes: what are the possible implications for the market microstructure, like tightening the bounds of circuit breaks, or international financial policies, such as an increased coordination by Central Banks? Ignoring potential contagion effects might also result in substantial utility losses for investors, see, for instance, Ang and Bekaert (2002).

In this paper we study the dynamics of the dependence structure between stock markets. In particular, we attempt to answer the following questions. Have the stock markets become more integrated over the last two and a half decades? Is there any evidence of contagion between the major stock markets, and, if so, what are the implications of the latter for the international portfolio diversification strategies? Did the markets become more interdependent after the October 1987 crash, and if so, was the increase in interdependence contagion driven?

We do not only investigate the magnitude of the impact of market integration and contagion on the interdependence structure of the markets, but we also investigate the question whether this impact is symmetric during the stock markets' joint up- and downturns, a question which has been surprisingly sparsely discussed in the existing literature.[1] While being an interesting theoretical issue in itself, this question is particularly important for investors who choose to diversify their portfolios internationally. In this context we draw a connection between the strand of literature investigating the dynamics of structural shifts in the stock markets comovements and a growing body of literature on the downside risk and related measures. We make use of Sklar's (1959) theorem, recently extended by Patton (2001), which allows us to decompose a multivariate distribution into its marginals and a dependence function or *copula*. We use a Markov Dependent Mixture of Copulas (MDMC) model, where the dependence structure shifts between three primitive regimes, which are modelled by three one-parameter copulas, with upper, lower, and zero tail dependence, and where the shifts are governed by first-order Markov chains, as in Hamilton (1989). By testing for the presence of an increase in market integration and contagion within each of these regime, and by evaluating their impacts, we aim to provide further insights into the dynamics of the stock market comovements.

Our main findings are as follows. First, we do not find empirical evidence that the US-Japan markets have become more integrated. But we do find strong evidence in favor of an increase in market integration between the US-UK and the US-Germany markets. Interestingly, for the UK-US pair this increase is significantly more pronounced in the upper tail regime, making an integration process favorable for investors, while the picture is the opposite for the US-Germany stock markets, which exhibit a sharp increase in the lower tail dependence over the last two and a half decades. Second, we find clear empirical evidence of the presence of contagion. In particular, we find that the markets tend to become significantly more interdependent during highly turbulent periods and economic recessions. Curiously, while increasing the lower tail regime dependence, we do not find a contagion effect in the upper tail dependence regime. We also quantify the potential utility loss for investors in case they do not account for this asymmetry, showing the importance of contagion for optimal portfolio choices. Finally, we find that all the markets under investigation became more interdependent after the October 1987 crash, but for different reasons. While for the US-Japan markets an increase in the comovement is contagion driven, and, thus, of temporary nature, in case of the US-UK markets the shift

[1] While some papers investigate the possible asymmetry of a contagion effect, we are not aware of any study that investigated and discussed the possible implications of an asymmetric market integration process.

in the interdependence structure appears to be permanent, due to the investors overreaction to the crash itself. In case of the US-Germany stock markets both investors' overreaction and contagion seem to contribute to an increase in these stock markets comovement.

The remainder of this paper is organized as follows. In Section 2.2 we briefly overview the existing literature on the stock markets integration and contagion. In Section 2.3 we describe the data and present the basic model that will be used in the subsequent analysis. In Section 2.4 we discuss the methodology. In Section 2.5 we present and discuss the estimation results. Section 2.6 illustrates the practical implications of neglecting contagion effects. Section 2.7 concludes. Appendices 2.A and 2.B contain a motivation for the models used in our empirical analysis.

2.2 Literature Review

2.2.1 Have Stock Markets Become More Integrated?

For a long time, the use of international diversification in portfolio choice has been advocated, the main reason being the relatively low correlations between national stock markets (see, for example, Solnik (1974)). The superior risk-adjusted performance of internationally diversified portfolios over domestic ones has been widely reported (see, for instance, McDonald (1973),Guy (1978), Grauer and Hakansson (1987), and Bauman *et al.* (1998)). Thus, understanding the dynamics of the correlation, and the long-run dependence structure between the financial markets is of crucial importance for choosing an optimal international portfolio strategy.

There is little doubt about the fact that during the recent two decades the economies have become increasingly globally oriented, both through more economic links, such as international trade, and through more financial channels, due to the removal of impediments to international investments. Cross-border foreign direct investments of the major industrial countries have grown from 82.8 billion US dollars in 1980 to 448.3 billion US dollars in 1997, and the portfolio cross-border investments have increased from 233.4 billion US dollars in 1985 to the impressive number of 764.3 billion US dollars in 1995 (IMF, 1998). This global trend towards economic integration leads to the question whether the stock markets have become more interrelated as well, and, if so, whether the benefits of international portfolio diversification are as significant as it is argued.

Naturally, most of the empirical work concentrated on studying the stability of the stock markets correlation matrix across the different time-periods. In his critical review Roll (1989) argues that " ...except for the period immediately around the 1987 crash, there is only meager evidence that international linkages across markets have become tighter over time". Ratner (1992) claims that the international correlation coefficients were stable during the period 1973-1989. On the other hand, Longin and Solnik (1995) find that the correlation coefficients between the major stock markets were upward trending over the period of 1960-1995. This result has been recently confirmed by Berben and Jansen (2005), who found a structural shift in the US-UK and the US-Germany stock markets correlation matrix.

However, the long-run increase in the economic and financial integration is not the only possible reason for the markets to become more closely related. Numerous studies claim that after the worldwide stock market crash of October 19, 1987, the markets have become more interdependent. During that day *all* major stock indices have simultaneously plummeted down. In fact, as it has been noticed by Roll (1989), October 1987 was the only month during the decade of the 1980-s when every market moved in the same direction. On the day of the crash, October 19, the S&P500 composite index plunged 22.9 percent, setting off international repercussions. On the next day, the NIKKEI 225 index declined 16.1% and other world markets experienced similar sharp price declines. During the two weeks of the crisis (October 19, and the preceding drop of October 14) the DAX and S&P 500 suffered a decline of 11%, the FTSE 100 lost 13.5% of its value, and the NIKKEI 225 lost only a "moderate" 6.1%.

The most intriguing feature of this crash is the absence of any reasonable explanation of what could be the cause for such an abrupt default of the stock markets around the world. Some authors attribute the crash to the fundamentals (for instance, Mitchell and Netter (1989)), while others argue that the crash was the burst of the speculative bubble of the mid-80-s (for instance, Siegal (1988)), lack of market liquidity (for example, Amihud *et al.* (1989)) or a global "contagion" scenario (for instance, King and Wadhwani (1990)). Among all these theories a "contagion" based explanation seems to be the most persuasive one. Shiller (1987, 1988) provides some survey evidence that there was no clear-cut reaction to any kind of announcement that triggered the crash. A lot of investors admitted that they had experienced "contagion or fear on the day of the crash". In case of Japan, the majority of investors considered the news about the crash to be the most important issue during the day of the crash, and, in general, the news from the US was ranked as being more important compared to the news from Japan itself. Seyhun (1990) studies the trading pattern of the insiders around the market crash and arrives at the conclusion that a sharp decline of the stock market has been caused by the overreaction and not due to the fundamentals.

Bertero and Mayer (1990) argue that the stock markets displayed a higher degree of interdependence both during and after the month of the crash. Malliaris and Urrutia (1992) report an increase in the contemporaneous causality between the major stock markets after the crash. Masih and Masih (1997) study the interdependence between the stock markets using a Vector Error Correction (VEC) framework and conclude that, in general, the crash brought about a greater interaction between the national stock markets. Koutmos and Booth (1995) study the mechanism of price and volatility spillovers between the New York, London, and Tokyo stock exchanges. They conclude that the linkages and the interactions among these markets have increased substantially during the post-crash era. Smith (1999) applies a cross-spectral analysis for the major equity markets and concludes that on average the coherence between the markets has substantially increased after the crash.

In Figure 2.1 we present the estimates of Kendall's tau for the major developed markets, estimated with a one-year rolling window. Both the Germany-US couple and the UK-US couple appear to become increasingly interdependent over time. The UK-US dependence structure also exhibits a sharp increase around the end of the 1980-s, which might be due to the October crash. On the other hand, in case of the US-Japan couple, the interdependence between the stock markets seems to be quite stable over the time. Of course, the issue is whether an increase in the interdependence structure observed in case of the Germany-US and UK-US couples was indeed the result of a statistically significant shift in the long-run dependence, or simply a temporary increase caused by short-run dynamics.

In general, the studies of market integration and the studies on the pre-and post-crash equity market linkages agree in one thing: the markets indeed have become more interdependent since the end of the 1980-s. However, whether this increase in interdependence should be attributed to the crash or to the globalization oriented policies of the recent two and a half decades is not

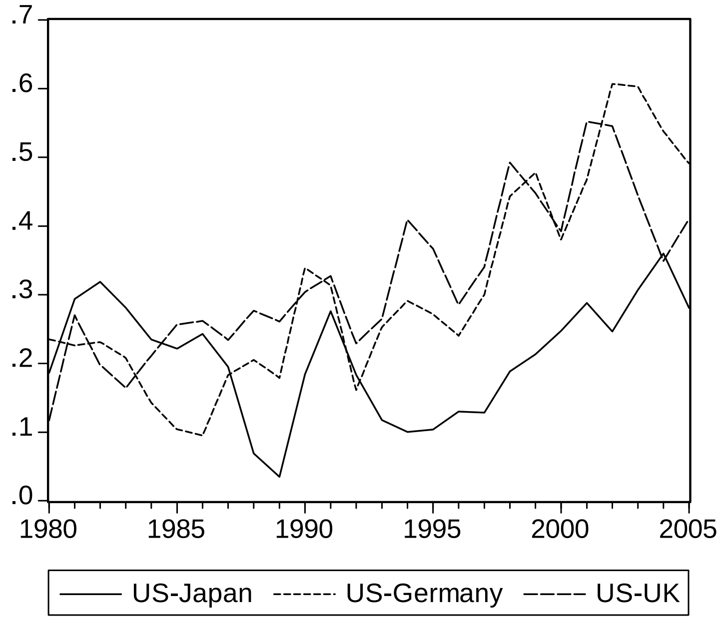

Figure 2-1: Empirical Kendals tau of the international vs US stock markets

straightforward, since both events happened during the same time period. Both a sudden shift in the dependence structure caused by the crash and a gradual adjustment of the dependence structure to a new and higher level of dependence could produce the shift in the different dependence measures mentioned above. Thus, to get further insight into the nature of this change, one should also study the dynamics of the latter.

We study the long-run dynamics of the linkages between the major stock markets in a Markov-Dependent Mixture of Copulas (MDMC) framework. Applying a smooth transition structural shift approach, introduced by Luukkonen *et al.* (1988) and Lin and Terrasvirta (1994) within our framework allows us both to test for the existence of a structural shift and to decompose the latter, if present, into a crash and long-run integration effects. In addition, the mixture of copulas framework allows us to test for symmetry of the structural shift, i.e., whether the event had its impact on both the upper and lower tail dependence regimes, or maybe only on one of them. Our results indicate that for the US-Japan markets there is no evidence of either a structural shift caused by the "Black Monday" crash or a time trend in the dependence structure which would be consistent with a long-run integration process. On the other hand, in case of the US-UK and US-Germany couples we find strong empirical evidence in favor of both an October crash impact, resulting in an upward shift of the left tail index, and an increase in the market integration, resulting in a gradual increase in both the upper and lower tail indices in case of US-UK and only the lower tail index in case of US-Germany. Interestingly, for these markets a shift in the interdependence structure appears to be asymmetric, a fact which potentially has an important implications for the international portfolio diversification strategies.

2.2.2 Have developed markets developed contagion?

During the last decade, financial markets around the world have been highly turbulent. Numerous currency crises followed by stock market crashes, including the "Tequila crash" in 1994 and the "Asian Flu" in 1997, have rapidly propagated from the originating country to other geographically distant economies, with seemingly no relationship in terms of fundamentals or in terms of trading or financial links. This phenomenon has shifted the interest of both economists and policymakers to an alternative driving force of financial market comovement, namely "contagion".

While there exists an extensive body of both theoretical and empirical literature, studying the contagion phenomenon, one can hardly find at most two researchers who agree on what contagion really means. The Worldbank proposes three alternative definitions of contagion:[2]

1) *Broad definition.* Contagion is a cross-country transmission of shocks or a general cross-country spillover effect. Contagion can take place both during "good" times and "bad" times and, thus, does not have to be related to a crisis. However, the presence of contagion is emphasized during crisis times.

2) *Restrictive definition.* Contagion is the transmission of shocks from some originating country to other countries, or the cross-country correlation, beyond any fundamental link among the countries, and beyond common shocks. This definition is usually referred to as an excess comovement, driven by herding instincts.

3) *Very restrictive definition.* Contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "tranquil times".

[2] See the World Bank Group website www.worldbank.org for a brief summary of the contagion literature.

Again, one can easily see that there is quite a thin line between these three definitions. For instance, if the "crisis period" has been caused by some global shock, say a sudden increase in oil prices, which has led to a simultaneous decline of the national stock markets, then an increase in the stock markets comovement can be defined as a contagion effect according to either the broad or the very restrictive definition. Thus, an important issue in studying contagion is a precise definition of what we define as the contagion phenomenon.

Fundamentals-based contagion is usually referred to as a crisis spreading from a country where the initial shock occured to other economies by means of real (trade) or financial links. The importance of bilateral trade links as a transmission channel of contagion has been stressed by Glick and Rose (1999). Financial links, on the other hand, are usually referred to as the situation when the investors holding internationally diversified portfolios are forced to sell the assets both in the market hit by the crisis and in the other markets, in order to keep up with margin requirements (Calvo (1998)). Alternatively, the crisis propagation mechanism can be explained by the existence of a common creditor country, which will respond to the crisis by the reduction in its credit lines in historically correlated economies (Folkerts-Landau and Garber (1998)).

An important class of models relate contagion to investors' behavior. In their seminal paper, King and Wadhwani (1994) present a model of international equity markets with incomplete information and with investors facing a signal-extraction problem. They show that this type of behavior creates a direct link between the magnitude of the international transmission of shocks and the volatility, resulting in a volatility driven contagion. Another strand of literature relates contagion to the existence of multiple equilibria (Obstfeld (1996)), where the currency devaluation is a sort of "preemptive strike", when the market is dominated by the sentiment that the currency will be depreciated, turning the investors' beliefs into self-fulfilling ones.

The world wide propagation of currency and stock market crises has also inspired an extensive body of empirical literature testing whether contagion is the reason for crises to become so widely spread. King and Wadhwani (1990) test for an increase in cross-market correlations between the US, UK, and Japanese equity markets, and find supporting evidence of an increase after the US stock market crash. This finding is supported by Lee and Kim (1993), who report an increase in cross-market correlations for twelve major financial markets. Baig and Goldfajn (1999) analyze cross-market linkages between the stock market returns, sovereign spreads, and exchange rates of five Asian countries before and during the "Asian Flu" (July 1997-May 1998). They find that for each variable under investigation there has been a significant increase in the cross-country correlations during the turbulent period of currency and stock market crisis. However, as shown by Forbes and Rigobon (1999), this traditional approach might result in upward biased estimates of the correlation coefficients during the turbulent periods, due to selection bias, thus, leading to overrejection of the null of no contagion and, thus, a downward correction for heteroscedasticity has to be made.[3] After correcting for heteroscedasticity these authors find almost no evidence for a correlation breakdown during the Mexican and Asian crises.

An alternative approach to control for the selection bias is by taking it into account by explicitly modelling the probability distribution of asset returns. Eichengreen *et al.* (1995) and Bae, Karolyi, and Stulz (2003) estimate the joint "tail" coexceedance probabilities using a probit and logit framework. This procedure involves choosing a threshold value for the negative (positive) "extreme" events, where the data is transformed into a binary variable taking the value 1 or 0, depending on whether the return is above or below the threshold. In both cases empirical evidence for contagion is reported.[4] Edwards and Susmel (2001) study the comovement of stock markets in Latin America and Asia during the Mexican and Asian crises using a bivariate SWARCH models and find strong evidence in favor of variance–state-dependent correlation coefficients, which is consistent with the signal-extraction model of King and Wadhwani (1994).

In this study we test for the presence of contagion between the major stock markets within a copula based framework which provides us with direct measures of positive (negative) crises, namely, the tail indices. Thus, in our framework, we define a lower tail contagion as a shift in the lower tail index conditional on a shift in the state of the economy (fundamentals based contagion) or conditional on an increase in the volatility of financial markets (pure or volatility based contagion). Upper tail contagion is defined in a similar way. We find strong empirical

[3] A similar remark has been made by Longin and Solnik (2001), who show that for the bivariate normal distribution with constant correlation, conditioning on large absolute values leads to an increase in the conditional correlation.

[4] As pointed out by Dungey *et al.* (2003), a sample-based choice of a threshold may result in a potentially non-unique classification of the data for different sample periods.

evidence in favor of both volatility and fundamentals based contagion for the US-Japan and US-Germany stock markets and also, though some weaker evidence, of contagion between the US-UK stock markets. We also quantify a potential utility loss for the investors who do not account for contagion effects which appear to be economically significant as well.

2.3 Data Description and Model Selection

In this section we first describe the data we use. Then we present the model that we will use in the subsequent sections to test for the presence of market integration and contagion effects.

2.3.1 Data Description and Preliminary Analysis

Our basic data set consists of closing stock index levels of the S&P 500 (United States), the FTSE 100 (United Kingdom), the DAX 30 (Germany) and the Nikkei 225 (Japan), all denominated in US dollars. The data has been obtained from Datastream. Our sample covers the period from January 1, 1980 to August 31, 2005, consisting of 1339 weekly Thursday-to-Thursday returns, calculated by taking first differences of the logarithmic indices levels.[5]. In addition, we include in our data set business cycle indicators as the state-of-economy variables of the markets mentioned above.[6] .

Table 1 presents descriptive statistics for the USD denominated returns. All variables are characterized by a high kurtosis. In case of the DAX 30, there is also some evidence of negative skewness. For the other series the skewness coefficient is insignificant. A Lagrange Multiplier (LM) test on serial correlation indicates the presence of autocorrelation for the DAX returns. An ARCH LM test indicates significant GARCH effects for all four return series. Based on the large values of Jarque-Berra statistic we strongly reject the null of unconditional normality for all four return series.

[5] Burns *et al.* (1998) show that aggregation to weekly returns in general allows to avoid the problem of the non-synchronous trading.

[6] These indicators are on a monthly basis. They have been purchased from the US Conference Board. For a full description of how these indices are comprised and other details, see www.conference-board.org.

Table 1: Summary statistics

	DAX 30		FTSE 100		NIKKEI 225		S&P 500	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Mean	0.0006	0.00037	0.0007	0.00028	0.0004	0.004	0.0007	0.0003
St.Dev	0.014	0.0005	0.012	0.00049	0.012	0.00047	0.01	0.0004
Skew	-0.35	0.14	-0.54	0.39	-0.03	0.125	-0.48	0.34
Kurt	5.48	0.65	8.62	2.01	4.39	0.3	6.9	2.08
S.Corr.LM	15.26**		5.85		5.26		3.6	
ARCH LM	137.14**		38.79**		98.31**		114.57**	
J-B. Stat	393.4**		1830.25**		109.53**		901.94**	

Descriptive statistics estimated jointly by (G)MM. Standard errors are Newey-West HAC with 7 lags.

S.Corr.LM denotes a Lagrange Multiplier test on serial correlation between returns

ARCH LM denotes a Lagrange Multiplier test on ARCH effects in volatility

J-B. Stat denotes Jarque-Berra test statistic applied to returns. *(**) indicates significance at 10 (5) %

To provide a first impression on a possible dependence structure between the series, we estimate for each pair of markets the empirical exceedance probabilities. We define the empirical exceedance probability $p_{j(-j)}$ as the (empirical) probability that market A will be above (below) its mean by more than j standard errors, conditional on the same state of market B. We take the US market as the conditioning market B and estimate the empirical exceedance probabilities over the range of four standard errors with a 0.1 grid, that is $j \in \{-4, -3.9, ..., 3.9, 4\}$. The results are presented in Figure 1. In general, both the Germany-US and the UK-US stock markets appear to be jointly negatively skewed. However, while the UK-US markets seem to have more power in the negative tail, the outcome is quite the opposite for the Germany-US pair: it seems to exhibit higher upper tail dependence. On the other hand, for the Japan-US pair the dependence structure seems to be quite symmetric, with no substantial asymmetry between upper and lower tail probabilities, which, in fact, seem to converge to zero.

In addition, for a first understanding on how the "tail" asymmetry is evolving over time, we also plot in Figure 2.2 the difference between the exceedance probabilities of $+(-)1.8$ standard errors, i.e., $p_{1.8} - p_{-1.8}$, using a rolling window of two years. All markets seem to exhibit a gradual increase in the negative asymmetry around the turbulent years 1988-1992 containing "Black Monday" of October 1987 and the currency crises during 1992-93 in Europe. This tendency seems to reverse during the mid-1990-s, possibly reflecting the enthusiasm of the "dot.com" bubble, and seems to become close to zero around the years 2002-2004 in case of the UK and Japan, while remaining negative for the Germany-US couple.

To summarize our preliminary analysis, we can say that for all the markets the dependence structure seems to exhibit a substantial degree of time variation. The interdependence between Germany-US and UK-US seems to be asymmetric, suggesting that modelling this interdependence using a standard (say, Gaussian or Student-t) framework may result in a serious misspecification. In addition, as is typical for many non-parametric estimators, the coexceedance probability- and asymmetry measure-estimates suffer from a high estimation inaccuracy, making it hard to reach specific conclusions regarding the characteristics of the interdependence structure between the markets. Notice, however, that these are unconditional estimates. It is possible that, while the unconditional joint distribution is symmetric, the conditional distribution, conditional on past information, is skewed. Therefore, while not imposing it, we shall allow for the possibility of asymmetry and time variation in our model, to be presented below.

2.3.2 The Model

Since copula theory allows us to decompose a joint distribution into its margins and a dependence function (the copula), it seems natural to select some "appropriate" model by conducting a separate specification search on the margins and on the whole distribution. If, for instance, the models of the marginal distributions perform well in specification tests, but the model of the joint distribution appears to be misspecified, then the source of the misspecification seems to be a wrong choice of the copula function. We first discuss the modeling of the margins, and then we turn to the modeling of the copula.

Specification of the Margins

The series exhibit an unconditional kurtosis which is significantly higher than the one implied by the normal distribution. We hypothesize that this can be due to:

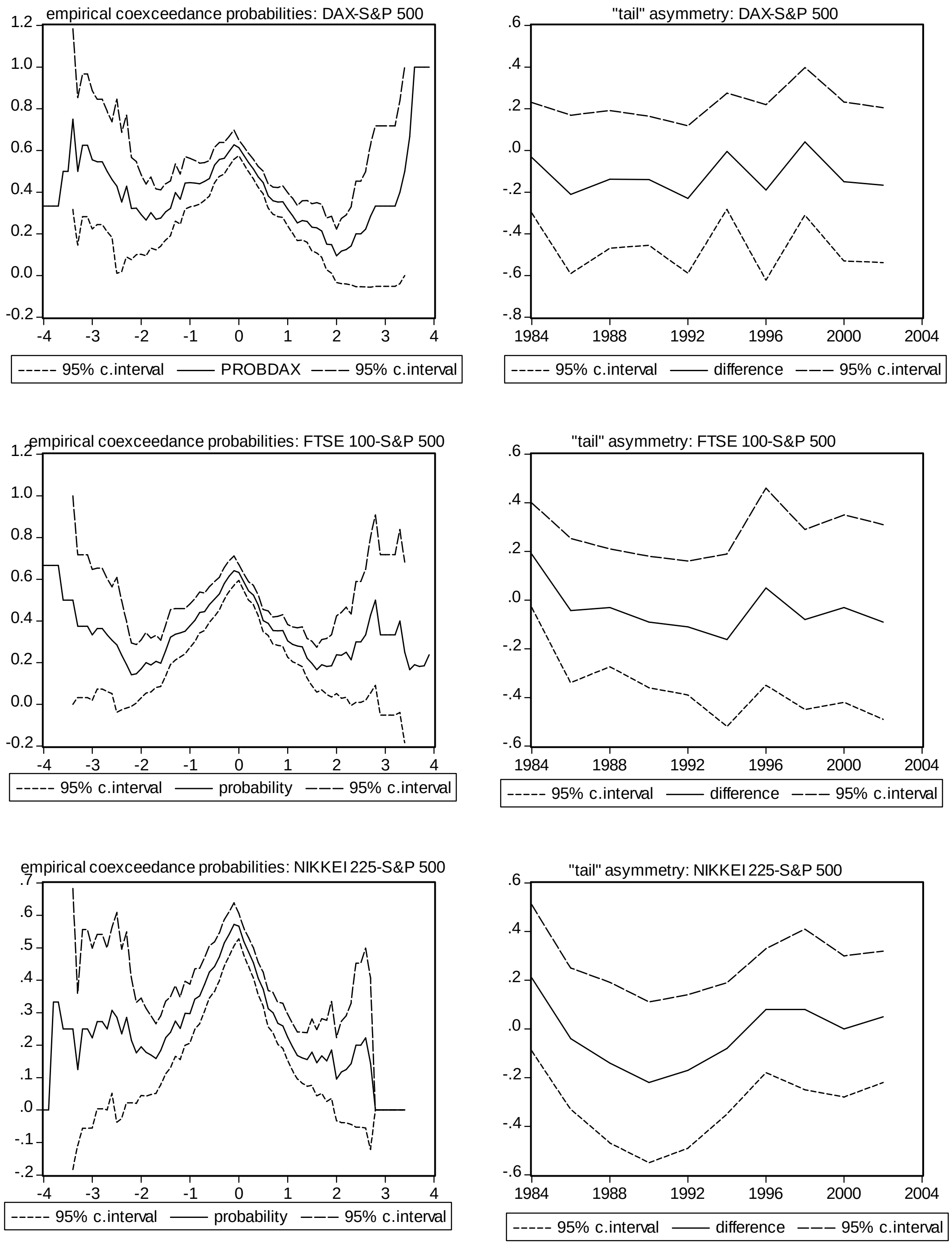

Figure 2-2: Empirical coexceedance probabilities and "tail" asymmetry.

a Non-normally distributed innovations

b GARCH effects with normally distributed innovations

c Both of them

To make our model sufficiently flexible, but at the same time also parsimonious, we model the margins by means of an AR(q)-GARCH(1,1) process (compare Ramchand and Susmel (1998), and Berben and Jansen (2005)) with possibly a leverage effect and Generalized Error Distribution (GED-) distributed innovations (Nelson (1991)):

$$\phi(L)X_t = \mu + \epsilon_t$$

$$\epsilon_t = h_t^{1/2} v_t$$

$$h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \gamma\epsilon_{t-1}^2 \cdot I_{t-1}$$

$$v_t \overset{i.i.d}{\sim} GED(\eta)$$

Here $\phi(L)$ denotes a lag-operator polynomial, I_t is an indicator function which takes the value 1 if $\epsilon_{t-1} < 0$ and 0 otherwise, and η is the shape parameter of the Generalized Error Distribution, with "fat tails" corresponding to $\eta < 2$ and "thin tails" to $\eta > 2$. For $\eta = 2$, the GED is the standard normal distribution. Based on an autocorrelation function (ACF-) analysis we include an AR(2)- term in the mean equations of the DAX and the Nikkei and no lags in case of the S&P 500 and the FTSE 100. Appendix 2 contains the specification search as well as the resulting margins used in the subsequent analysis.

Specification of the Copula/the Joint Distribution

Based on our preliminary data analysis, it seems reasonable to model the dependence structure in a framework which allows for both symmetry and time variation in the tail indices. One way of achieving this goal might be to model the dependence structure using a two-parameter copula framework. The problem, however, is that for most two-parameter copulas the tail indices are interdependent, a fact which would limit the flexibility too much. An alternative approach, advocated here, is to model the dependence structure by means of a time-dependent mixture of one-parameter copulas. Consider three simple one-parameter copulas, C_U, with positive upper tail dependence but no lower tail dependence, parametrized, say, by $\lambda_U > 0$ and $\lambda_L = 0$, C_L, with zero upper tail dependence and positive lower tail dependence, i.e., $\lambda_U = 0$ and $\lambda_L > 0$, and C_0 with no upper and lower tail dependence, i.e., $\lambda_U = \lambda_L = 0$. Then we can consider as copula at time t, conditional upon the available information at time $t-1$, the copula C_t, defined as $C_t = C_U$, with conditional probability $p_{U,t}$, $C_t = C_L$, with conditional probability $p_{U,t}$, and $C_t = C_0$ with conditional probability $p_{0,t} = 1 - p_{U,t} - p_{L,t}$. Then from the point of view of an observer who makes inferences based on the information set at time $t-1$, both the conditional upper and lower tail indices can be strictly positive, since they are equal to $p_{U,t}\lambda_U$ and $p_{L,t}\lambda_L$, respectively, obviously nesting symmetry as a special case.

Modelling the dependence structure using this conditional mixture framework, we still have to choose the functional form of the copulas and the probability law governing the time evolution of the copulas' conditional probabilities or weights (the p-s). For C_U we choose the Gumbel copula, for C_L we choose the Clayton copula, and for C_0 we choose the Frank copula (see Appendix B for a brief description of these copulas). Among the Archimedean class of copulas these are the copulas which are most widely used due to their simple closed form and nice analytical properties (see, for instance, Valdez (2001), Longin and Solnik (2001) Henessey and Lapan (2002) and Smith (2003), among others). In addition, we shall assume that the probability law governing the regimes can be described by a first-order ergodic Markov process with time-invariant transition probability matrix P with typical component p_{ij} denoting the probability of entering next period regime j given that currently the system is in regime i, where $i, j \in \{0,\ U,\ L\}$, so that, for example,

$$\begin{aligned} p_{U,t} &= p_{U,0}, \text{ in case of regime 0 at time } t-1, \\ &= p_{U,L}, \text{ in case of regime } L \text{ at time } t-1, \\ &= p_{U,U}, \text{ in case of regime } U \text{ at time } t-1. \end{aligned}$$

Since the seminal paper of Hamilton (1989) Hidden Markov Models have become a widely used tool in empirical modelling of the behaviour of financial markets (see, for instance, Ryden *et al* (1998), Ramchand and Susmel (1998), Gordon and St-Amour (2000) to name a few) due to their ability to capture endogenous breaks in the distributional properties of asset prices. As shown in Appendix B, this model is strongly superior compared to the Gaussian and Student-t copulas, frequently used in empirical research, and it also performs quite well in specification tests.

2.4 Methodology

2.4.1 Testing for the Long-Run Trend in the Interdependence Structure

Since changes in the dependence structure cannot reliably be detected by simply splitting the sample based on data realizations (see, for instance, Boyer (1999)), we allow for a smooth transition (ST) between two different dependence measures, following Lin and Terrasvirta (1994), and Berben and Jansen (2005). A smooth transition from low to high market intedependence is also consistent with the concept of increasing market integration, which is more likely to be a gradual process rather than an abrupt shift in the dependence structure.

Our model consists of a time-varying mixture of the one-parameter copula

$$C_t = p_{U,t}C_U + p_{L,t}C_L + (1 - p_{U,t} - p_{L,t})C_0$$

with a deterministically varying dependence parameter within each regime

$$\theta_t^j = \theta_1^j \Psi(\gamma^j(s_t - c^j)) + \theta_2^j(1 - \Psi(\gamma^j(s_t - c^j))),\ j \in \{0, L, U\}$$

where

$$s_t = \frac{t}{T}$$

and

$$\Psi(x) = \frac{1}{1 + \exp(x)}.$$

In this setup, γ^j can be interpreted as the speed of the structural break, and c^j tells us when "on average" a structural break occurred (Berben and Jansen (2005)). As an extension of the methodology by Berben and Jansen (2005), we test for an increase in market integration within each regime separately. In case the markets become more integrated over time, one would expect the dependence parameters to be trending upwards. However, it may be the case that the trend is asymmetric, with a trending upward left tail parameter and a time-constant right-tail dependence parameter, or that both tail indices are trending upwards but with different speeds. This distinction is crucial for investors who would be interested not only in whether the markets tend to move more closely together, but also whether an increase in comovement occurs during only an up- or a downturns or both. While a standard Gaussian ST model[7] is unable do distinguish between these cases, these possibilities are special cases within the framework presented here.

Clearly, before estimating a ST version of the Markov-dependent mixture, one should test for the existence of a deterministic trend within one or more of the regimes. Time-constancy of the dependence parameters can be obtained by setting $\theta_1^j = \theta_2^j$ within each regime j, or by setting γ^j equal to zero, for all the regimes $j \in \{0, L, U\}$. Thus, under the null, some of the parameters remain unidentified, implying that the standard tests are inapplicable. To solve the identification problem, we follow the Taylor series-approximation approach proposed by Luukkonen *et al.* (1988), by modelling an "auxiliary" ST model where the weighting function $g(s_t; \gamma, c) \equiv \Psi(\gamma(s_t - c))$ is replaced by its first-order Taylor series approximation $\widetilde{g}(s_t; \gamma, c)$ around $\gamma = 0$:

$$\widetilde{g}(s_t; \gamma, c) = \frac{1}{2} - \frac{\gamma}{4}(s_t - c) + R(\gamma),$$

where the remainder term $R(\gamma)$ is of order γ^2. After plugging this approximation into our original ST model, the following representation for each dependence parameter can easily be derived

$$\theta_t^j = \widetilde{\theta}^j + \widetilde{\gamma}^j s_t,$$

where $\widetilde{\theta}^j = \frac{1}{2}(\theta_1^j + \theta_2^j) + \frac{1}{4}\gamma^j c^j (\theta_1^j - \theta_2^j)$ and $\widetilde{\gamma}^j = \frac{1}{4}\gamma^j c^j (\theta_2^j - \theta_1^j)$.(see also Berben and Jansen (2005)). A standard LM test for testing the null hypothesis $\widetilde{\gamma}^j = 0$, corresponding to dependence constancy within regime j, can then easily be constructed.

An alternative scenario for the long-run dynamics is a sudden shift in the dependence structure, because of some extreme event, such as the October crash of 1987. Numerous studies indicate that around the date of this crisis the markets became more interdependent. A

[7] See, for instance, Berben and Jansen (2005).

question which naturally arises, is whether the impact of the crash was completely transitory, fully permanent, or maybe a combination of these two, i.e., a sudden shift in the dependence structure immediately after the crash, with a subsequent gradual adjustment of the market interdependence to its original level (a semi-permanent impact) or to a new level (a long-run increase in market integration). To model these possibilities, we assume that within each regime $j \in \{0, L, U\}$ the dependence parameter evolves according to the equation

$$\theta_t^j = (\theta_1^j I_{bc} + \theta_2^j I_{ac}) \cdot \Psi(\gamma^j (s_t - c^j)) + \theta_3^j \cdot (1 - \Psi(\gamma^j (s_t - c^j)))$$

where I_{ac} is the indicator function which takes the value 1 for observations after October 19, 1987, and zero otherwise (an "after crisis" dummy), and I_{bc} (the "before crisis" dummy) takes the value 1 for observations up to and including the crash week, and zero otherwise. Then a completely transitory impact, i.e., a constant dependence structure within a regime, results in the null hypothesis

$$H_0 : \theta_1^j = \theta_2^j = \theta_3^j \text{ or } \theta_1^j = \theta_2^j \;\&\; \gamma^j = 0$$

while a permanent impact yields as null hypothesis

$$H_0 : \gamma^j = 0.$$

Again, after approximating $g\left(s_t; \gamma, c\right) \equiv \Psi\left(\gamma(s_t - c)\right)$ by $\widetilde{g}\left(s_t; \gamma, c\right)$, and some algebraic manipulations, the following equations to be used in testing, can be obtained

$$\theta_t^j = \widetilde{\theta}_1^j + \widetilde{\theta}_2^j I_{ac} + \widetilde{\theta}_3^j s_t - \widetilde{\theta}_4^j I_{ac} s_t$$

with

$$\widetilde{\theta}_1^j = \frac{1}{2}(\theta_1^j + \theta_3^j) + \frac{1}{4}\gamma^j c^j (\theta_1^j - \theta_3^j)$$

$$\widetilde{\theta}_2^j = (\theta_2^j - \theta_1^j)(\frac{1}{2} + \frac{1}{4}\gamma^j c^j)$$

$$\widetilde{\theta}_3^j = \frac{1}{4}\gamma^j (\theta_3^j - \theta_1^j)$$

$$\widetilde{\theta}_4^j = \frac{1}{4}\gamma^j (\theta_2^j - \theta_1^j)$$

Then, testing the null of a permanent vs a semi-permanent change boils down to testing the null of $\widetilde{\theta}_3^j = \widetilde{\theta}_4^j = 0$, and testing for dependence constancy is equivalent to testing $\widetilde{\theta}_2^j = \widetilde{\theta}_3^j = \widetilde{\theta}_4^j = 0$. Since, obviously, the model with constant parameters is nested within the model with a permanent structural break, and the latter is a special case of the semi-transitory model, we proceed in two steps. First, for each pair of markets we test the null of dependence constancy against the alternative of a permanent break via the LM test for the standard ST model. At the second stage, for those markets where the null of dependence constancy has been rejected, we estimate an auxiliary model under the restriction $\gamma^j = 0$, and test the null of a permanent vs a semi-permanent break via the LM test, by applying it to the scores of the auxiliary model. For those markets where the null of dependence constancy vs the alternative of permanent impact has not been rejected, we estimate an auxiliary model under the restriction $\widetilde{\theta}_2^j = \widetilde{\theta}_3^j = \widetilde{\theta}_4^j = 0$, and then test the null of the dependence constancy vs the alternative of a semi-permanent break, again via the LM test with the scores of the auxiliary model.

2.4.2 Testing for the Presence of Contagion

We define contagion as a shift in the dependence structure between stock markets as a result of a shift in the volatility or a change in a state of economy. Since contagion is usually associated with a crisis period, we concentrate our attention on the propagation mechanism of extreme positive (negative) shocks from one stock market to another, the tail dependence indices. In order to test for the presence of contagion, we find it useful to consider the following reparametrization of the dependence parameters for the Gumbel and Clayton copulas, which in our framework, represent the dependence regimes with upper and lower tail dependence, respectively,

$$\theta_{U,t} = \frac{\log(2)}{\log(2 - \lambda_{U,t})}$$

$$\theta_{L,t} = -\frac{\log(2)}{\log(\lambda_{L,t})},$$

where the conditional upper and lower tail indices are parametrized as a logistic function of the state of the economy (Z_e) and the volatility shift covariates (Z_h)

$$\lambda_{U,t} = \frac{\exp(\mu_u + \phi_{us,u} Z_{us,t} + \phi_{f,u} Z_{f,t} + \phi_{h,u} Z_{h,t})}{1 + \exp(\mu_u + \phi_{us,u} Z_{us,t} + \phi_{f,u} Z_{f,t} + \phi_{h,u} Z_{h,t})}$$

$$\lambda_{L,t} = \frac{\exp(\mu_l + \phi_{us,l} Z_{us,t} + \phi_{f,l} Z_{f,t} + \phi_{h,l} Z_{h,t})}{1 + \exp(\mu_l + +\phi_{us,l} Z_{us,t} + \phi_{f,l} Z_{f,t} + \phi_{h,l} Z_{h,t})}$$

In this framework, the no volatility based (or "pure") contagion hypothesis corresponds to the case where $\phi_{h,u} = \phi_{h,l} = 0$, while the no contagion case is obtained by setting all ϕ-s equal to zero. Also, note that, while nesting as a special case symmetric volatility effects in case of both positive and negative shocks, similarly as in King and Wadhwani (1990), we also allow for an asymmetric impact on the upper and lower tail indices.[8]

Obviously, a particularly important issue is the choice of covariates. Since the volatility based contagion is usually considered as an abrupt shift in the interdependence, we introduce a threshold GARCH effect within the dependence structure of our model. Specifically, we define the indicator function $Z_{h,t}$ as follows

$$Z_{h,t} = \begin{cases} 1 \text{ if } h_{A,t} > T_A \text{ and } h_{B,t} > T_B \\ \quad\quad 0 \text{ otherwise,} \end{cases}$$

where T_A and T_B denote the threshold values for markets A and B, respectively.[9] In other words, we allow both upper and lower tail indices to shift in case both markets are expected to be highly turbulent during the next period. Since, by definition, tail indices are invariant with respect to which market we define as the economy where initial shock has occured, it is important to concentrate on the joint volatility of the markets and not on the separate volatilities effects.

As discussed above, the fundamentals based propagation mechanism of shocks between the stock markets depends (at least in theory) on various macroeconomic and financial variables, such as the trade balance, openness of the economy to foreign capital inflows and outflows,

[8] Bae, Karolyi and Stulz (2003) report mixed evidence on the asymmetric contagion effects.
[9] A slightly different type of threshold effect has been used by Longin and Solnik (1995).

etc., which obviously are not available at a weekly or monthly frequency. Therefore, we use a Conference Board Coincidence index which describes an overall level of the economic activity and also is published on monthly basis [10] As with the volatility based contagion, we define the following indicator functions

$$Z_{f,t} = \begin{cases} 1 \text{ for decrease in "foreign" business cycle} \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{us,t} = \begin{cases} 1 \text{ for decrease in US business cycle} \\ 0 \text{ otherwise} \end{cases}$$

where "foreign" stands for Germany,UK, or Japan, depending on which pair of market is studied, and an increase (decrease) in the business cycle indicators is measured as a log-difference between the level of the indicator in the current and preceding months. In other words, we allow for "jumps" in the upper and lower tail indices, due to a high turbulence or worsening economic conditions.

Two issues should be kept in mind in case of this "generalized" contagion model. First, note that by including the state of the economy indicators in our model, we extend the information set, on which we condition the joint distribution of stock market returns. That is, our information set $\mathcal{F}_{t-1}$ now includes the whole history of the returns of both stock markets *and* the information regarding the state of both economies, on which we should condition *both* the margins and the copula. To keep our model parsimonious, we allow the state of economy variables to affect the conditional mean of the stock market returns by including the state of the economy covariates $Z_{f,t}$ and $Z_{us,t}$ in the conditional mean equations for each stock market. Second, it is important to realize that the business cycle indicators are reported with a time delay. For instance, the US business cycle indicators for October are published at the end of November, while the Germany, UK, and Japan business cycle composites generally become available at the end, middle, or beginning of December. Taking this time-lag into account is important for a proper definition of information available to the investors.

[10] The data, at a monthly frequency, has been purchased from the Conference Board (www.conference-board.org) and transformed into weekly frequency by simply taking the same value of the indicator for all the weeks of the particular month.

2.5 Empirical Findings

In this section we present and discuss our empirical findings. In subsection 2.5.1 we test for the presence of and estimate the long-run trends in the dependence structure of the developed stock markets. Next, we test for the presence and examine potential implications of contagion for the comovement between the stock markets in subsection 2.5.2

2.5.1 Testing for and Estimating the Long-Run Trends in the Interdependence Structure

We begin with presenting and discussing the results of the structural shift tests as discussed in Section 2.4. In the upper panel of Table 2 we present the p-values of the LM test for a single smooth structural break, which may be consistent with an increase in market integration. For each pair of markets the test has been performed both for the individual regimes and for the entire dependence structure. The results clearly indicate that, in general, the null of no time-trend cannot be rejected at any legitimate level of significance. However, it is possible that the time path of a structural change has been subject to abrupt shifts, such as the October crash of 1987, which has not been detected by the ST LM test. Therefore, we next turn to the two-stage testing procedure for the semi-permanent structural break as described above.

The p-values of the two-stage procedure are presented in the middle and lower panels of Table 2, respectively. The high p-values clearly indicate that for all pairs of markets the null of a constant dependence parameter vs a permanent break, in general, cannot be rejected for any of the three copulas.[11] In addition, there is no evidence for a semi-permanent shift for the US-Japan markets. On the other hand, there is strong empirical evidence in favor of a semi-permanent structural shift in the upper tail (the Gumbel copula, $j = U$) and there is also, somewhat weaker, evidence of a semi-permanent shift in the lower tail dependence regime (the Clayton copula, $j = L$) in case of the UK-US and US-Germany markets.

In order to assess the robustness of our results, we conduct the following test. For every copula, where a structural shift has been detected, we calculate the LM test statistic over the entire range of the observations by shifting a presumed structural break date by a window of

[11] We have also conducted a joint LM test for the whole distribution function which is asymptotically distributed under the null as χ^2_3. The results are very similar to the individual copulas tests.

50 observations (i.e., approximately one year) both backward and forward with respect to the crash date (thus, shifting forward and backward the indicator function I_{ac}). As a result, for each copula we obtain a series of LM test statistics. For both the US-UK and US-Germany couples, the Clayton copula - LM test statistics remain significant only in the neighborhood of the crash, supporting the idea that both a shift caused by the October crash and long-run dynamics are present in the lower tail dependence structure. On the other hand, the Gumbel copula LM statistics is above the critical values over the entire range, implying that the upper tail dependence structure most likely is subject to a gradual rather than an abrupt change. Thus, for the US-UK markets we estimate the model with a semi-permanent shift in both the Gumbel ($j = U$) and Clayton ($j = L$) copulas and for the US-Germany couple the semi-permanent shift is allowed only in the Clayton copula.

Table 2:Results of the structural break tests

	S&P-DAX	S&P-FTSE	S&P-NIKKEI
2.1: Smooth structural shift			
Gumbel (U)	0.85	0.96	0.96
Clayton (L)	0.84	0.81	0.91
Frank (0)	0.79	0.46	0.92
2.2: Permanent structural shift			
Gumbel (U)	0.75	0.96	0.59
Clayton (L)	0.39	0.93	0.93
Frank (0)	0.54	0.88	0.67
2.3: Semi-permanent structural shift			
Gumbel (U)	0.83	0.009	0.14
Clayton (L)	0.007	0.07	0.52
Frank (0)	0.76	0.89	0.31

In this table we present the results of the structural break tests under three alternative scenarios, as discussed in Section 2.4. The reported numbers are the corresponding p-values for each scenario, for each dependence regime, and for each pair of the stock markets respectively

Next, we present the estimation results of the ST-MDMC model applied to the US-UK and the US-Germany markets and the standard MDMC model applied to the US-Japan markets. For the sake of saving space we only present the estimates of the time-varying parameters of the copulas. For each pair of markets and for each copula we present the equation which governs the evolution of the corresponding copula over time. For the US-UK pair both upper and lower tail regimes are characterized by a low degree of dependence before the crash (in case of the Gumbel copula the markets seem to be nearly independent). In case of the Gumbel copula the Black Monday crash has resulted in a very moderate upward shift in the upper tail dependence, a finding which supports the results of the robustness test, implying that the October crash had no permanent impact on the upper tail regime. However, the picture is completely reversed for the lower tail regime, where the October crash has resulted in a significant increase in the dependence parameter, which has been followed by the gradual adjustment to the new and higher level of interdependence, consistent with a long-run integration process. These findings are also in line with the classical overreaction picture, namely, that the investors became more sensitive to the "bad" news immediately after the crash (see Figure 2.3). For both copulas the difference between θ_1 and θ_3 is statistically significant, supporting the idea that over time the markets became more integrated. Interestingly, there is also a statistically significant difference between the speed of adjustment coefficients (the γ-s) which is much higher for the Clayton copula than for the Gumbel copula, possibly implying that the investors are more sensitive to bad news than to good news.[12]

US-UK

$$\text{Gumbel copula: } \theta_t^U = (\underset{(0.08)}{1.0002} I_{bc} + \underset{(0.51)}{1.024} I_{ac})\Psi + \underset{(0.2)}{1.774}(1-\Psi)$$
$$\text{with weight: } \Psi(\underset{(6.84)}{6.01}(s_t - \underset{(0.22)}{0.4}))$$
$$\text{Clayton copula: } \theta_t^L = (\underset{(0.5)}{0.81} I_{bc} + \underset{(0.39)}{1.04} I_{ac})\Psi + \underset{(1.04)}{10.2}(1-\Psi)$$
$$\text{with weight: } \Psi(\underset{(28.93)}{34.31} \cdot (s_t - \underset{(0.05)}{0.86}))$$
$$\text{Frank copula: } \theta^0 = \underset{(1.28)}{1.5}$$

US-Germany

$$\text{Gumbel copula: } \theta^U = \underset{(0.18)}{2.21}$$
$$\text{Clayton copula: } \theta_t^L = (\underset{(0.16)}{0.292} I_{bc} + \underset{(0.32)}{0.67} I_{ac})\Psi + \underset{(0.43)}{1.72}(1-\Psi)$$
$$\text{with weight: } \Psi(\underset{(232.1)}{312} \cdot (s_t - \underset{(0.02)}{0.55}))$$
$$\text{Frank copula: } \theta^0 = \underset{(0.42)}{2.17}$$

US-Japan

$$\text{Gumbel copula: } \theta^U = \underset{(0.08)}{1.12}$$
$$\text{Clayton copula: } \theta^L = \underset{(0.17)}{0.38}$$
$$\text{Frank copula: } \theta^0 = \underset{(1.19)}{3.32}$$

$^{\perp}$Standard errors in parentheses

[12] The speed of adjustment coefficients have been estimated as $\gamma^j = (\delta^j)^2$, to keep them positively. The high estimation inaccuracy of the γ^j-s is partially due to the delta method based standard errors, and also due to the fact that a wide range of γ^j-s can produce almost the same Ψ (see Lin and Terrasvirta (1994)).

For the US-Germany pair, as in the case of the US-UK pair, the markets appear to be almost independent in the lower tail dependence regime at the beginning of the 1980-s. As in the case of the US-UK markets the October Crash resulted in a sharp increase in the lower tail index. However, in contrast to a rather gradual market integration process, as it appears in the US-UK case, in case of the US-Germany couple the adjustment to a new dependence level is almost immediate and occurs around 1992-1993. Compared to these markets the US-Japan pair exhibits a remarkably stable dependence structure with Kendall's tau ranging between 0.16 and 0.24, though exhibiting some long-run swings, possibly due to the dependence cycles (see Figure 5). Also, for the US-Japan pair both upper and lower tail regimes appear to be nearly independent, with low and statistically insignificant dependence parameters of the Gumbel and Clayton copulas, implying that the Japanese stock market is less integrated with the US market than the European markets.

An important issue is whether the long-run market integration process is symmetric or whether it exhibits some degree of asymmetry. This issue is particularly important in the face of recently repeated statements that the recent globalization oriented trend increases the comovement between equity markets and, thus, reduces the benefits from international diversification. However, neither correlation coefficients nor any other overall measure of interdependence does provide us with information regarding the *direction* of this increase, thus, implicitly assuming that the increase has been symmetric, or that the investors have mean-variance preferences, or any other type of preferences which solely depend on the overall measures of risk. There is a growing body of evidence that a downside risk, that is, a probability that the value of the portfolio will fall below some threshold level, plays an important role in portfolio selection decisions (see, for instance, Harvey and Siddique (2000) and Ang, Chen, and Xing (2004)). Both one-sided constraints, such as short-selling restrictions and institutional and banking regulations, such as the Value at Risk, imply that partial dependence measures are much more important than an overall measures of dependence. In addition, numerous experimental evidence supports the prospect theory of Kahneman and Tversky (1979) and the disappointment aversion theory of Gul (1991), suggesting that individuals tend to treat gains and losses differently. Our findings, however, suggest that for the US-UK markets the long-run integration process not only increased the overall dependence between the financial markets, but also increased the probability of a joint positive comovement compared to the probability of observing a joint negative comovement, which, in light of the evidence mentioned above, implies that the integration process of the US and UK stock markets appears to be *favorable* for the majority of investors. On the other hand, for the US-Germany markets the integration process resulted in an increase in the lower tail index, increasing the probability of joint negative comovements, leading to a significant reduction of the international diversification benefits.

To demonstrate this point for the US-UK and the US-Germany markets, we plot the time path of the "booming-crash" odds, which we define as the ratio between the upper and lower tail indices ($p_{U,t}\lambda_U$ and $p_{L,t}\lambda_L$). In other words, we analyze the ratio between the probability that market A will boom, given that market B is booming as well, and the probability that market A will crash, given that market B has collapsed. This ratio provides useful information about the tail behavior of a portfolio comprised of these two market indices and, thus, allows us to analyze the impact of both the October crash and the market integration on the benefits of international diversification strategies. In order to concentrate solely on the long-run effects, we replace the time-varying upper and lower regimes filter probabilities by their ergodic estimates which are equal to 0.384 and 0.127, respectively, for the US-UK markets, and 0.141 and 0.35 for the US-Germany markets.

The results are presented in Figure 2.3. For the US-UK markets the odds appear to be upward trending until the end of 1990-s, with an abrupt downward shift due to the October crash. From the end of 1990-s, the odds exhibit a reversed trend, reaching the "steady state" level (ignoring short-run dynamics) of 1.67 compared to 0.6 at the beginning of the 1980-s, exhibiting an increase of almost 200%, implying that, due to the market integration process, US-UK diversified portfolios became conditionally more positively skewed. On the other hand, for the US-Germany markets both the October crash and the market integration process resulted in an abrupt downward shift in the odds, leading to a reduction from 2.73 at the beginning of the 1980-s to 0.38 by the middle of 2005.

To summarize this section, a number of important findings should be mentioned. By applying a smooth-transition methodology as proposed by Luukkonen *et al.* (1988) to the MDMC model we find strong empirical evidence of a long-run market integration process in case of the US-UK and the US-Germany stock markets since the beginning of the 1980-s. For these markets

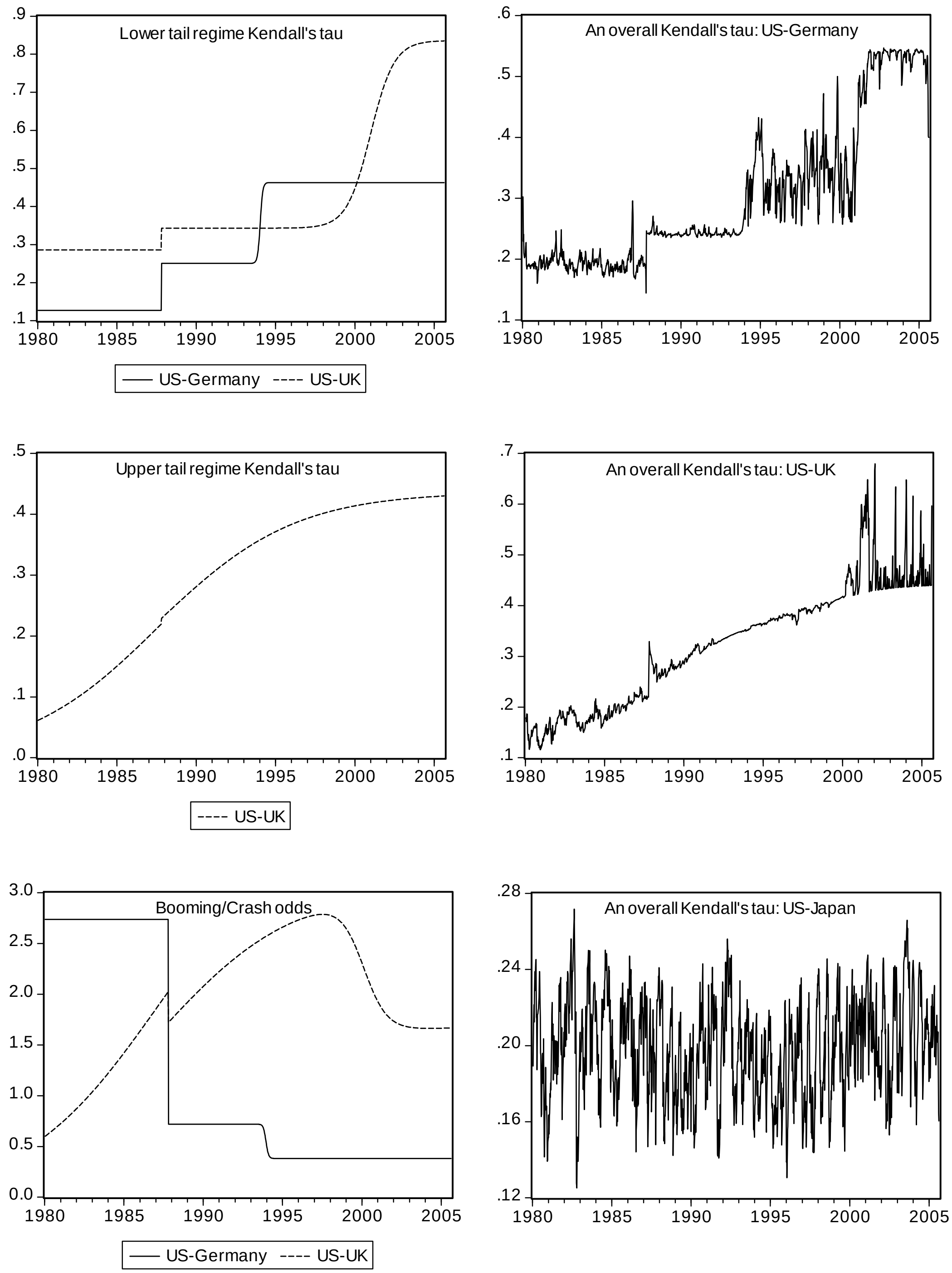

Figure 2-3: Long-run integration, October Crash and the dependence structure of the stock markets

we also find a solid empirical evidence of a structural break in the lower tail index, following the October crash. Our results also suggest that in case of the US-UK markets an increase in the market integration resulted in a decrease in the downside risk, a finding which has important implications for the optimal portfolio choice, making the diversification between these two markets more favorable. On the other hand, in case of the Germany-US stock markets, an increase in the market integration resulted in an increase in the downside risk, potentially leading to a significant reduction of the benefits for a diversification between these two markets. Consistent with other related studies no evidence for a time-trend or a permanent shift in the dependence structure of the US-Japan stock markets has been found. However, an interdependence structure can also be subject to the temporal shifts, caused by short-run dynamics, such as contagion. This will be the issue of the following subsection.

2.5.2 Testing for and Estimating Contagion Phenomenon

In this subsection we estimate and examine the impact of contagion phenomenon on the comovement between the major developed stock markets. For each pair of markets we estimate two models: a "pure" or volatility based contagion model where the tail indices are allowed to be volatility dependent and a "generalized" model where both volatility based and fundamentals types of contagion effects are allowed, as discussed in Section 4. The reason for this distinction is that we are also interested in testing whether the volatility based contagion effects, reported by other authors, are indeed driven by volatility or that these effects are simply due to the fact that financial markets become increasingly turbulent during economic recession periods and, therefore, can be considered as a fundamentals based contagion as well.

Table 3 presents the estimation results of the "pure" contagion and generalized contagion models. As the volatility threshold value we chose the three times unconditional volatility of the GARCH (1,1) model.[13] For the sake of saving space, only the estimates of the tail indices (which constitute the main interest of this section) are reported.

The estimation results of the "pure" contagion model indicate that in case of the UK-US markets both contagion coefficients are insignificant, implying that the null of no "pure" contagion cannot be rejected. This finding is in line with Longin and Solnik (1995) and Ang

[13] The results are fairly robust to different choices of the threshold value.

and Bekaert (2002a). Also, for Japan-US and Germany-US the upper tail contagion coefficients are insignificantly different from zero. On the other hand, we find a strong empirical evidence for these markets in favor of the lower tail volatility contagion, where the contagion coefficients are positive and significant. It is particularly important to emphasize the economic significance of the volatility contagion effect. In case of the Germany-US couple, turbulent periods result in an increase in the lower tail dependence index, conditional on being in the lower tail dependence regime, from 0.114 to 0.645. The increase in the overall lower tail dependence is substantial as well, shifting from a moderate 0.014 to 0.08 percents. The impact of volatility in case of Japan-US is even more striking. Conditional on being in the lower tail dependence regime, the lower tail dependence index increases from 0.05 to approximately 0.5 during the turbulent periods.

In order to assess the importance of the contagion effects it may be useful to go back to the October crash of 1987. In the previous section we found that the "Black Monday" crash resulted in an upward shift in the interdependence structure for the US -UK and US-Germany stock markets, while no such evidence could be found in case of the US-Japan markets. On the other hand, numerous papers indicate that after the crisis, these markets became more interdependent. An alternative explanation could be a temporary shift in the dependence structure due to contagion effects.

In Figure 2.4, we plot the overall Kendall's tau implied by the "pure" contagion model for the Japan-US stock markets around the crash date. As can be clearly seen, during and up to about seven months after the crash these markets have been characterized by unusually high volatility and also by an increased interdependence. Our estimation results also indicate that during this period the stock market volatilities indeed exceeded the threshold. These findings support the view that a reason for the October crisis to become so widely spread was contagion and the temporal increase in stock market intedependence was partially contagion based.

Table 3: Contagion models

		S&P-DAX		S&P-FTSE		S&P-NIKKEI	
		Coeff.	Std Error	Coeff	Std Error	Coeff	Std Error
"Pure" contagion model	μ_u	0.44	0.12	-0.25	0.11	-0.98	0.97
	$\phi_{h,u}$	0.27	0.26	0.61	0.44	-5.01	98.22
	μ_l	-2.05	0.61	1.07	0.26	-2.98	1.52
	$\phi_{h,l}$	2.65	0.78	-0.51	1.46	3.01	1.52
	Log-ld	8664.17		8841.3		8491.45	
Generalized contagion model	μ_u	0.38	0.15	-0.17	0.13	-0.98	0.67
	$\phi_{h,u}$	0.15	0.28	0.56	0.46	-2.31	5.23
	$\phi_{f,u}$	0.14	0.23	-0.02	0.32	-0.38	0.86
	$\phi_{us,u}$	0.16	0.27	-0.13	0.3	-0.05	0.89
	μ_l	-4.99	1.48	0.8	0.29	-2.94	1.62
	$\phi_{h,l}$	5.62	1.29	-0.16	1.29	2.98	1.61
	$\phi_{f,l}$	2.68	1.06	-5.76	9.27	-0.14	0.7
	$\phi_{us,l}$	2.06	1.03	1.15	0.41	1.28	0.73
	Log-ld	8665.72		8848.74		8494.13	

In this table we present the maximum likelihood estimates of contagion models for each pair of the stock markets. The specifications considered are the pure and generalized contagion models

Pure contagion model: $\lambda_{U,t} = \frac{\exp(\mu_u+\phi_{h,u}Z_{h,t})}{1+\exp(\mu_u+\phi_{h,u}Z_{h,t})}$, $\lambda_{L,t} = \frac{\exp(\mu_l+\phi_{h,l}Z_{h,t})}{1+\exp(\mu_l+\phi_{h,l}Z_{h,t})}$

Generalized model: $\lambda_{U,t} = \frac{\exp(\mu_u+\phi_{us,u}Z_{us,t}+\phi_{f,u}Z_{f,t}+\phi_{h,u}Z_{h,t})}{1+\exp(\mu_u+\phi_{us,u}Z_{us,t}+\phi_{f,u}Z_{f,t}+\phi_{h,u}Z_{h,t})}$, $\lambda_{L,t} = \frac{\exp(\mu_l+\phi_{us,l}Z_{us,t}+\phi_{f,l}Z_{f,t}+\phi_{h,l}Z_{h,t})}{1+\exp(\mu_l++\phi_{us,l}Z_{us,t}+\phi_{f,l}Z_{f,t}+\phi_{h,l}Z_{h,t})}$

Here, $\lambda_{U,t}$ and $\lambda_{L,t}$ are the time-varying upper and lower tail indices of the Gumbel and Clayton copulas, $Z_{h,t}$ is the indicator function of the volatility threshold and $Z_{us,t}$ $(Z_{us,t})$ is the indicator function of the US (foreign) business cycle.

Next, we also present the estimation results of the generalized contagion model, where the tail indices are allowed to be affected by both volatility and fundamentals. Since preliminary estimation of the business cycles composite loadings in the mean equations yielded highly insignificant estimates for all the markets, we decided to exclude the state of the economy covariates from the margins. For the UK-US and Germany-US markets a decrease in the US

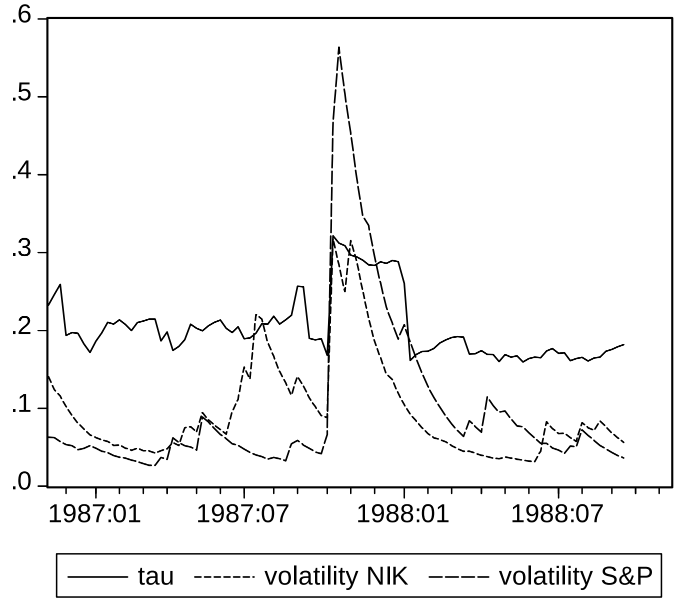

Figure 2-4: Volatility based contagion and October Crash: US-Japan stock markets

business cycle indicator results in an empirically significant increase in the lower tail index, with p-values calculated from the Table 3 equal to 0.045 and 0.005, respectively. There is also some (though weaker) evidence of a fundamentals based contagion in case of the Japan-US markets with p-value of the US business cycle indicator coefficient equal to 0.08. On the other hand, as in the case of volatility contagion, there is no empirical evidence in favor of positive quadrant contagion, where the coefficients are both economically and statistically insignificant. It is noteworthy that for the Germany-US and Japan-US markets the coefficients of the volatility based contagion remain significant after controlling for the fundamental effect implying that an increase in the stock markets interdependence due to a high turbulence or a change in the economic conditions are two potentially distinct phenomena.

To provide some intuition regarding the significance of volatility and fundamentals based contagion for each pair of markets we plot the coexceedance probabilities, as we defined them in section 2.3. As in section 2.3, we distinguish between positive and negative coexceedance probabilities. An important difference is that here we plot *conditional* coexceedance probabilities implied by the model, where a distinction is made between no contagion, volatility based contagion, and volatility and fundamental contagion. That is, $p_{j(-j)}$ without contagion is defined as the conditional probability that the return on market A will be above (below) its mean by more than j standard deviations, conditional on the same state for market B when there is neither "excess" market turbulence nor decrease in economic activity. By allowing for the stock markets' volatilities to pass the threshold we estimate $p_{j(-j)}$ in the presence of the volatility based contagion. Allowing, in addition, for the decrease in the coincidence index gives us the estimate of $p_{j(-j)}$ when both volatility based and fundamental contagion are taken into account. As in the previous sections, we take the US stock market as market B and replace the time-varying filter probabilities by their ergodic estimates. For the Germany-US and Japan-US stock markets we present both volatility and volatility and fundamental contagion effects, while for the UK-US case we present the fundamental contagion effect alone, since for these markets a volatility based contagion appears to be both economically and statistically insignificant.

The coexceedance probabilities plots are presented in Figure 2.5. As for the UK-US stock markets, the impact of worsening economic conditions on the dependence structure appears to be quite weak, the result which holds for both positive and negative quadrant contagion, where, for the range higher than 4 standard errors, the coexceedance probabilities virtually coincide. This follows directly from the estimation results which show that there is no significant contagion effect on the upper tail index and there is weak effect on the lower tail index which increases from 0.12 to 0.l5. The results, however, are strikingly different for the Germany-US and Japan-US markets which appear to be characterized by a strong asymmetry of both volatility and fundamental contagion effects. While being economically significant for the moderate range (up to 2 standard errors) of the coexceedance, the impact of contagion quickly decays and becomes almost zero for the positive quadrant coexceedance probabilities. This comes in sharp contrast with the negative quadrant contagion effects. For instance, the probability that the German stock market will plunge down by more than six standard deviations, given the same condition for the US stock market, is about 0.3 during turbulent periods and 0.4 during the turbulent periods followed by an economic recession, while being almost zero during the tranquil periods. A similar picture can be observed in case of the Japan-US markets, with 0.1, 0.4, and almost 0 probabilities, respectively. It is important to note that, though, generally, contagion effects are discussed in the context of joint comovement of extreme realizations, they also appear

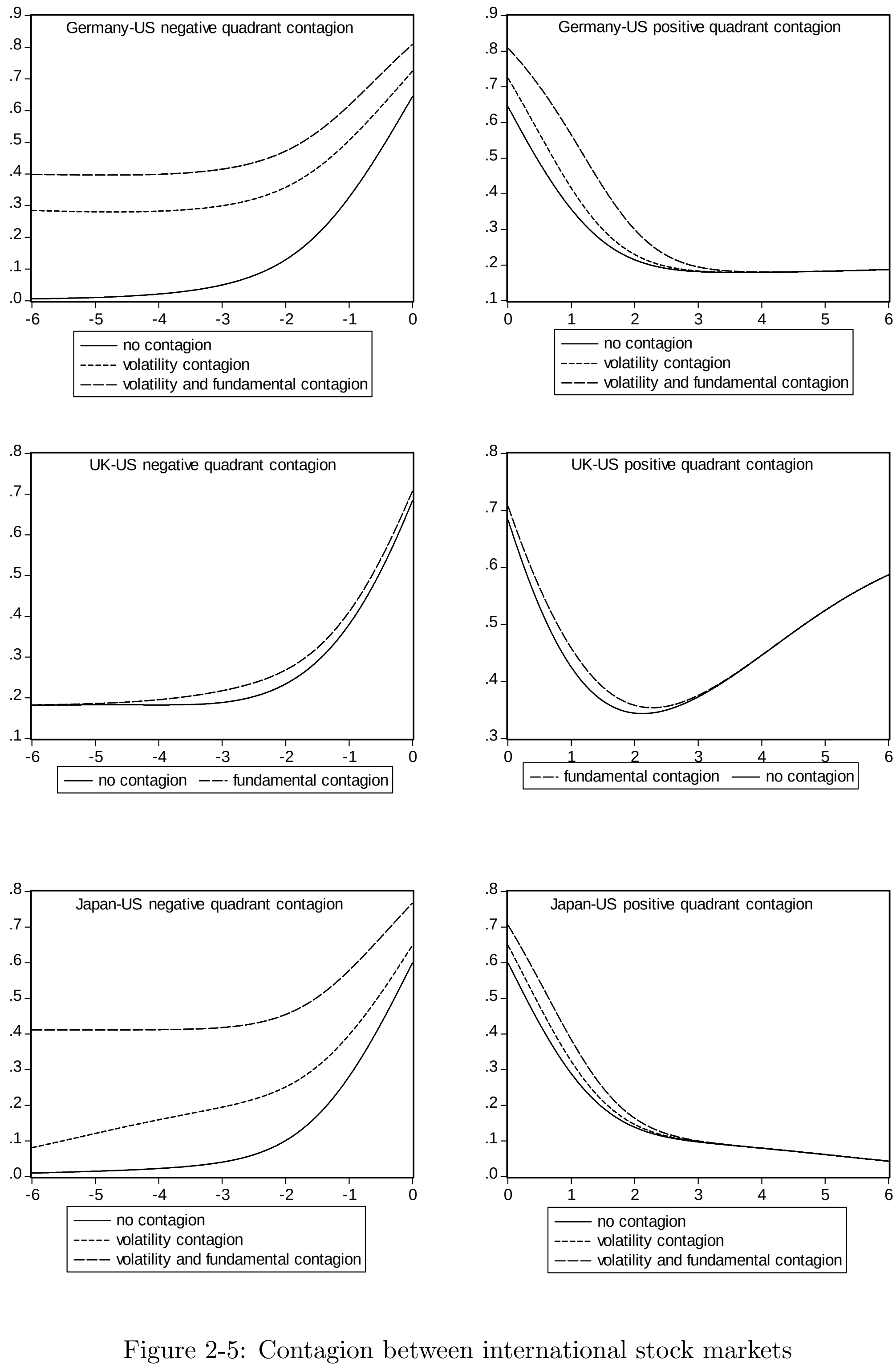

Figure 2-5: Contagion between international stock markets

to be economically significant in the "moderate" coexceedance regions. Consider, for instance, the estimated probability that the return of market A will be below its mean by at most one standard deviation, given the same condition for the US market. In case of a no contagion scenario for the Germany-US, UK-US, and Japan-US markets, the estimates are 0.435, 0.475, and 0.395, respectively. Conditional on a high expected turbulence, these estimates increase to 0.5 and 0.42 for Germany-US and Japan-US, while, in case of both a high turbulence and worsening fundamentals, $p_{(0,-1)}$ is equal to 0.647 and 0.51, respectively. Consistent with our earlier findings, in case of the UK-US markets contagion effects in the moderate range of coexceedance are weak as well, resulting in an increase in $p_{(0,-1)}$ from 0.475 to 0.517.

2.6 Contagion - Practical Implications

The practical implications of our findings are quite straightforward. Neglecting the contagion effects (particularly those which appear to be both statistically and economically significant) might result in potentially severe deviations from the optimal portfolio choice. Not taking into account the jumps in the dependence structure might lead to a systemic overestimation of the stock market interdependence during the tranquil periods and/or the periods of economic recovery, while possibly resulting in an underestimation of the former during turbulent periods or during economic recessions. As a result, investors might tend to overvalue (undervalue) the benefits from international diversification during turbulent (tranquil) periods, possibly shifting from cross-industry to cross-market portfolios, and vice versa, resulting in potential significant losses of utility. Moreover, taking into account the presence of contagion, while not accounting for its asymmetric nature (for instance, by estimating the state-dependent correlation coefficients as in Edwards and Susmel (2001), or the threshold-dependent correlations as in Longin and Solnik (1995), or by using any other state-dependent overall measure of dependence), in general, might cause the investor to overestimate the benefits of the international diversification as well. What is then the potential utility loss for an investor who either does not take into account the contagion effect or disregards its asymmetric nature? We quantify this by means of the following simple numerical example.

Consider a simple one-period optimal portfolio choice where the investment opportunity set consists of a domestic and a foreign broad market index with log-returns r_a and r_b, respectively, and a risk-free asset with log-return r_f. Further, let us assume that the investor's preferences can be described by a utility index of CRRA type

$$U(W) = \frac{W^{1-\gamma}}{1-\gamma}$$

where $W = \alpha_a \exp(r_a) + \alpha_b \exp(r_b) + \alpha_f \exp(r_f)$ denotes the investor's wealth at the end of the single period. Then the vector of optimal portfolio weights $\alpha^* = \left(\alpha_a^*, \alpha_b^*, \alpha_f^*\right)'$ is given by

$$\alpha^* = \arg\max_{\alpha} E_p(\frac{W^{1-\gamma}}{1-\gamma})$$

where E_p denotes expectation under the "true" probability measure, which takes both contagion and its asymmetric effects into account, corresponding to the "generalized" contagion model. The vector of portfolio weights of an investor who does not take contagion into account, and who maximizes the expected utility using a model with no contagion effects (that is, all ϕ-s are equal to zero) is denoted by α_n. Similarly, the vector of "optimal" portfolio weights of an investor who does not take into account the asymmetric nature of contagion (that is, the investor estimates a "generalized" contagion model under the restriction that the ϕ-s are equal in both tail indices) is denoted by α_s.

We set γ being equal to 5 and the risk-free rate to 3% in annual terms. Following Ang and Bekaert (2002a), we calculate the ammount of wealth $\widetilde{w}$ required to compensate an investor for using suboptimal portfolio weights, i.e., α_n or α_s instead of α^*. For instance, for the "contagion ignoring" investor $\tilde{w}$ is given by:

$$E_p(U(W^* \,|W_0 = 1)) \, = E_p(U(W_n \,|W_0 = \widetilde{w}_n))$$

The compensation required in cents per dollar of wealth can be expressed as $w = 100 \cdot (\widetilde{w}_n - 1)$.

Table 4: Compensation (cents per 1$)

	$p_U = 0.375, p_L = 0.25$		$p_U = 0.25, p_L = 0.5$		$p_U = 0.125, p_L = 0.75$	
	No cont.	Sym. cont.	No cont.	Sym. cont.	No cont.	Sym. cont.
US-Germany	2.5	2.53	2.7	2.8	3.04	3.04
US-UK	0.02	0.02	2.4	1.08	2.62	2.27
US-Japan	0.01	0.02	0.07	0.08	0.04	0.21

In this table we calculate a compensation required for ignoring contagion effects or its asymmetric nature. Compensation is expressed in cents per dollar of investment for an investor who completely ignores contagion effects (No cont.) and for an investor who ignores the asymmetry of contagion effects (Sym. cont). Compensation is calculated for three different sets of the upper and lower tail dependence regime probabilities p_U and p_L

The results are presented in Table 4. For each pair of markets we find a required compensation for using α_n and α_s, instead of the optimal portfolio weights, under three different sets of conditional regime probabilities. For the US-Germany markets the cost of completely ignoring contagion is extremely high, varying between 2.5 and 3.04 cents per dollar. The magnitude of utility loss is especially striking if we take into account that our calculations are based on a one-period model, and, thus, the cost will be expected to increase with an increase of the investment horizon. For the US-Japan markets the compensation for ignoring contagion is substantial as well, though of a lower magnitude. Naturally, the compensation tends to increase with an increase in the lower tail regime probability. Ironeously, the cost of completely ignoring contagion and the cost of taking it into account while ignoring its asymmetric nature are almost the same. While at first sight this may seem surprising, it is quite intuitive since, by ignoring the asymmetry of contagion, we "smooth" the magnitude of the shift in the lower tail index between the upper and the lower tails. By doing so, we overestimate the former, while underestimating the latter, an operation which naturally causes the investor to overestimate the benefits of international diversification as in case of completely ignoring contagion effects.

2.7 Summary and Conclusions

In this paper we study the dynamics of interdependence between the major stock markets of the world. We make a distinction between long-run dynamics, namely the market integration process, and short-run dynamics, namely contagion. We model the dependence structure of the stock markets in a Markov-dependent mixture of copulas framework, which allows for both asymmetry and time variation in the tail indices.

Our major findings are

a) The US-UK and US-Germany stock markets have become significantly more interdependent over the last two and a half decades, due to the market integration process. No evidence of time-trend has been found in case of the US-Japan stock markets.

b) The implications of the market integration process for the international portfolio diversification benefits vary between the markets. While an increase in the US-Germany stock market comovement reduces the benefits of cross-market diversification, in case of the US-UK markets an increase in the stock markets comovement appears to be favorable for investors.

c) We find strong empirical evidence of contagion between the major stock markets. In particular, we document an increase in stock markets comovements during economic downturns and periods of high market turbulence. Interestingly, the contagion effects are asymmetric. The costs of ignoring contagion or ignoring its asymmetric nature appear to be economically significant.

d) The stock markets became significantly more interdependent after the October crash of 1987, but the nature of, and the reasons for the shift in the stock markets comovement appear to be different. While for some markets an increase in the interdependence has been mainly contagion driven, for others it seems to be the result of investors' overreaction to the crash itself.

By extending the existing literature on market integration and contagion in a number of different aspects, our findings also raise a number of important questions. Why are the contagion effects asymmetric? Does this reflect investors' loss aversion? What determines the magnitude of the contagion effects (microstructure, transaction costs)? Which global factors became more important, leading to an increase in market integration? All these, and other issues, will require further research.

2.A Specification of competing models

a Gaussian (Normal) copula.

For the conditional Gaussian copula we adopt the structure proposed by Patton (2001) with slight modification in the equation of the correlation evolution

$$C_N(u, v/\Omega_{t-1}) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{(1-\rho_t^2)}} \exp\left\{ \frac{-\left(s^2 - 2\rho_t st + t^2\right)}{2(1-\rho_t^2)} \right\} dsdt$$

with the time evolution of the correlation coefficient described by the following equation

$$\rho_t = \Lambda(\kappa_1 + \kappa_2 \rho_{t-1} + \kappa_3 \sum_{i=1}^{10} \frac{11-i}{10} |u_{t-i} - v_{t-i}|)$$

where u_t, v_t are the integral transforms of the conditional marginal densities as specified above, Φ^{-1} denotes pseudo-inverse of the Standard Normal distribution and $\Lambda(x) = \frac{1-\exp(x)}{1+\exp(x)}$ in order to keep the correlation coefficient in $(-1, +1)$ range. The upper and lower tail dependence coefficients for the conditional Gaussian copula are

$$\lambda_{L,t} = \lambda_{U,t} = 0$$

implying asymptotic conditional independence.

b Student-t copula.

$$C_T(u, v/\Omega_{t-1}) = \int_{-\infty}^{t_v^{-1}(u)} \int_{-\infty}^{t_v^{-1}(v)} \frac{1}{2\pi\sqrt{(1-\rho_t^2)}} \left\{ 1 + \frac{s^2 - 2\rho_t st + t^2}{v(1-\rho_t^2)} \right\}^{-\frac{v+1}{2}} dsdt$$

with t_v^{-1} denoting a pseudo-inverse of Student-t distribution with v degrees of freedom. We assume the same time evolution equation for the correlation coefficient as in Gaussian case and keep the number of dof constant to make the comparisson of these two models more tractable. The upper and lower tail dependence coefficients for the conditional Student-t copula are

$$\lambda_{L,t} = \lambda_{U,t} = 2t_{v+1}(-\sqrt{v+1}\sqrt{1-\rho_t}/\sqrt{1+\rho_t})$$

Note that though we keep the number of degrees of freedom constant, time variation in the tail indices is allowed due to the time varying correlation.

c Markov Dependent Mixture of Copulas

$$C(u, v\,|\Omega_{t-1}) = p_{U,t}C_U + p_{L,t}C_L + (1 - p_{U,t} - p_{L,t})C_0$$

Gumbel copula

$$C(u, v; \theta) = \exp(-\left[(-\ln(u))^{\theta} + (-\ln(v))^{\theta}\right]^{1/\theta})$$

with $\theta \in [1, \infty)$ and upper tail index equal to $2 - 2^{1/\theta}$. The Gumbel copula exhibits left tail independence.

Clayton copula

$$C(u, v; \theta) = \left\{u^{-\theta} + v^{-\theta} - 1\right\}^{-1/\theta}$$

with $\theta \in [0, \infty)$ and lower tail index equal to $2^{-1/\theta}$. The Clayton copula exhibits right tail independence.

Frank copula

$$C_F(u, v; \theta) = -\tfrac{1}{\theta}\ln\left(1 + \tfrac{(e^{-\theta u}-1)(e^{-\theta v}-1)}{e^{-\theta}-1}\right)$$

with $\theta \in (-\infty, \infty)$ and $\lambda_U = \lambda_L = 0$. The Frank copula exhibits asymptotic independence in both tails.

Conditional regime probabilities can be calculated using the Hamilton (1994) filter. The upper and lower tail dependence coefficients for this model are

$$\lambda_{U,t} = p_{U,t} \cdot (2 - 2^{1/\theta})$$

$$\lambda_{L,t} = p_{L,t} \cdot 2^{-1/\theta}$$

2.B Evaluation of the Margins and Copula

For the evaluation of the margins we adopt the test suggested by Diebold *et al.* (1998) who show that a time sequence of integral transforms of correctly specified conditional density should be distributed iid U(0,1) over time. Following their suggestion we divide this test into two separate steps. First, we test the null of the independence by the BDS test of Brock, Dechert, and Sheinkman (1987) to the integral transforms of the estimated density function. The test for the uniformity is conducted by looking at the plot of the empirical distribution and its confidence interval. Though this test is conditional on the estimated parameters values, it appears to perform quite well in Monte-Carlo studies (see Diebold *et al.* (1998) for futher details).

As specification test for the copula and joint distribution function we apply a so-called "hit-test" suggested by Cristoffersen (1998) and extended by Engle and Manganelli (1999) and Patton (2001) which tests the ability of the model to predict whether the future realization of a random variable will be in a particular range. The major advantage of this test is that testing the predictive power of a model in different regions provides us with important clues about what is wrong with the model if the null of correct specification is rejected.

In addition, we compare the performance of our model to the performance of the Gaussian and Student-t copulas. We base our comparisson on the test proposed by Rivers and Vuong (2002) who show that a properly scaled averaged difference between the evaluation criterions (in our case log-likelihood values of the non-nested models) asymptotically has a standard Normal distribution. The scaling factor can be easily computed using the Newey-West approach.

Table B.1 presents the results of the BDS test performed on the integral transforms of the conditional marginal densities. The results show that the null of independence of the integral transforms cannot be rejected for all the markets included in our study. In addition, we study the empirical distributions of the integral transforms. The null that integral transforms are uniformly distributed cannot be rejected for all the markets. Overall, these findings suggest that GARCH-GED model fits the data reasonably well.

Table B.1: BDS independence test

	Dimension	2	3	4	5
DAX 30		0.481 (0.507)	0.253 (0.276)	0.299 (0.326)	0.281 (0.31)
FTSE 100		0.249 (0.263)	0.189 (0.202)	0.324 (0.327)	0.246 (0.241)
Nikkei 225		0.753 (0.713)	0.885 (0.823)	0.784 (0.741)	0.649 (0.617)
S&P 500		0.946 (0.966)	0.852 (0.825)	0.689 (0.75)	0.741 (0.812)

The numbers are asymptotic and bootstraped p-values based on 5000 replications.

Under the null of correct specification of the density function the integral transforms are i.i.d. distributed

Bootstraped p-values are in parentheses.

In Table B.2 we present the estimated parameters of the GED-GARCH margins for each one of the markets.[14]. For all the series the shape parameter η is significantlly smaller than 2, implying that the null of normally distributed innovations can be rejected. The persistence parameters in the volatility equations (Lag h_t and Lag ϵ_t^2) are highly significant indicating the typical phenomenon of volatility clustering. In addition, for all the series the leverage effect (Lever.) is highly significant implying that the effect of past innovations is sign dependent.

[14] Since we estimate the models in a single step ML framework, for each model we also obtain the estimates of the margins. However, since they appear to be very similar we report the estimates of the margins estimated separately from the copulas in order to save the space.

Table B.2: Estimates of the marginal distributions

	DAX 30		FTSE 100		NIKKEI 225		S&P 500	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Const$_\mu$	0.0008	0.0003	0.0007	0.0003	0.0007	0.0003	0.0009	0.0002
AR(2)	0.044	0.0288			0.056	0.028		
Const$_{h_t}$	$6.7 \cdot 10^{-6}$	$1.5 \cdot 10^{-6}$	$1.9 \cdot 10^{-5}$	$3.3 \cdot 10^{-6}$	$6.7 \cdot 10^{-6}$	$1.9 \cdot 10^{-6}$	$4 \cdot 10^{-6}$	$1.1 \cdot 10^{-6}$
Lag h_t	0.841	0.023	0.75	0.038	0.856	0.024	0.85	0.028
Lag ϵ_t^2	0.071	0.027	0.037	0.029	0.037	0.018	0.03	0.022
Lever	0.063	0.031	0.102	0.05	0.141	0.034	0.15	0.03
η	1.49	0.073	1.25	0.04	1.597	0.092	1.56	0.073
Log-ld	4024.2		4201.91		3972.07		4443.35	

In Table B.3 (a) we also present the results of the hit-tests applied to each one of the copulas. As testing regions we chose the lower 20%-20% region (denoted as Region 1 in the table), the upper 20%-20% region (Region 3) and the 40%-60% region (Region 2) based on the empirical quantiles of the series. The first two regions will give some indication on the capability of the model of predicting the joint extreme realizations, while the third one tests the goodness-of-fit with respect to the "normal" realizations.[15]

For all markets a Gaussian copula is rejected using both the individual "extreme" regions tests and the joint tests. The main reason for the misspecifications appears to be a systematic underestimation of the upper and lower tails probabilities, suggesting that the zero tail dependence imposed by the Gaussian copula is too restrictive. The performance of the Student-t copula is somewhat better. For the UK-US pair it passes all the individual and the joint test. However, for the Germany-US pair it does not pass the lower "extreme" region test and the joint test while for the Japan-US pair it does not pass both the lower and average regions tests, and also fails to pass the joit test.

Compared to these competing, frequently used models a Markov-Dependent Mixture model provides a significant improvement in fitting the data. Both for the Germany-US and UK-US pairs it passes all the individual and the joint tests. For Japan-US it passes the upper and the

[15] One can also add the regions with asymmetric extremes, but in our case the number of such observations is extremely small (even zero in some cases).

average region tests, but fails the lower region test. It is noteworthy that the reason for rejecting the null of correct specification is that the coefficient of the cumulative sum of the lower tail extremes is highly significant, suggesting possible higher order-dependence than the first-order dependence imposed by the model. This can be due to a contagion effect which, combined with volatility clustering, may result in time-dependent parameters within dependence regimes.

Table B.3: Goodness-of-fit tests

Table B.3(a):Results of the hit-test

		S&P-DAX	S&P-FTSE	S&P-NIKKEI
Gaussian	Region 1	0.014	0.028	0.000
	Region 2	0.058	0.754	0.434
	Region 3	0.000	0.001	0.342
	Joint	0.000	0.008	0.29
Student-t	Region 1	0.076	0.279	0.001
	Region 2	0.151	0.746	0.042
	Region 3	0.019	0.074	0.133
	Joint	0.022	0.351	0.007
MDMC	Region 1	0.075	0.308	0.003
	Region 2	0.81	0.747	0.871
	Region 3	0.641	0.091	0.354
	Joint	0.131	0.356	0.019

Table B.3(b): Rivers and Vuong (2002) equivalence test

	S&P-DAX	S&P-FTSE	S&P-NIKKEI
Gaussian	3.03 (0.001)	2.89 (0.002)	2.16 (0.015)
Student-t	2.83 (0.002)	2.09 (0.018)	0.167 (0.433)

$^{\perp}$The numbers in Table B.3 (a) are the p-values of the LR test. In Table B.3 (b) the numbers are the R&V statistics with p-values in parentheses.

The results of Rivers and Vuong (2002) test are presented in Table B.3 (b). We separately evaluate the performance of MDMC model versus Gaussian and Student copulas for each pair of markets under the investigation. The results indicate that the null of equivalence of MDMC and Student-t copulas is strongly rejected for both US-UK and US-Germany stock markets in favor of Markov-mixture model, which is quite consistent with the results of hit-test, the result which olso holds for the Gaussian copula. In case of US-Japan the MDMC model also outperforms (though insignificantly) a Student-t copula, while significantly outperforming the Gaussian copula.

Chapter 3

It Takes Two to Tango: International Transfer of Pricing Information Between the Cross-Listed Securities

3.1 Introduction

The purpose of this paper is to study the mechanism of pricing information transmission between cross-listed securities, that is, stocks of the same firm listed on multiple markets. Globalization oriented policies accompanied by a removal of impediments to international investments led to an increasing number of companies from overseas that have chosen to either raise capital through global equity issues or prepare for future capital raising by cross-listing. Already in 1997 about 1300 foreign companies had their shares listed on the US stock exchanges which constitutes an increase of 75 percent since 1991 (Karolyi (1998)).

Studying the dynamics of the information transfer between the securities listed on multiple markets is important for several reasons.When an identical asset is traded on more than one location we would expect the price discovery process to be global rather than local. First, when an asset is traded on multiple markets investors will attempt to extract the information from the "foreign" prices of the same asset in addition to the news revealed at their own market (see, for instance, King and Wadhwani (1990)). Second, if cross-border trading is allowed any substantial deviation from the price equality likely will rapidly vanish by opening an arbitrage opportunity. Thus, studying the pricing process of cross-listed securities allows us to study to which extent stock markets are efficient in reflecting new information. Studying the patterns of the information transmission between multiple listed shares may also reveal important clues on the role of the stock markets' micro-structure in the trading process and in the degree of inter-market integration (Werner and Kleidon (1996), Harris, McInish and Wood (2002)).

In this research we investigate the information transfer mechanism between American Depositary Receipts (ADRs) of Japanese corporations traded on the New York stock exchange and their underlying shares listed on the Tokyo Stock Exchange, two of the major stock exchanges in the world. We seek to contribute to the current state of literature in a number of ways.

First, we propose to investigate the information transfer mechanism by studying the transmission of the first three moments of the returns distribution, namely mean, volatility, *and* skewness. While most of the studies concentrate on the transmission of returns it is not so clear why the analysis should be limited to the investigation of the dynamics of the first moment only. Numerous studies relate the volatility to the dynamics of the information flow. There is also a growing body of evidence that a downside risk, that is, a probability that the value of the portfolio will fall below some threshold level, plays an important role in portfolio selection decisions (see, for instance, Harvey and Siddique (2000) and Ang, Chen and Xing (2004)), suggesting the importance of accounting for the skewness as well.

Second, we study the role of trading volume in the cross-markets return spill-over. A number of theoretical contributions suggest the existence of such a link (Campbell *et.al* (1993), Blume, Easley, and O'Hara (1994), Wang (1994)). In Campbell *et al.* (1993) the trading volume provides an additional information to the external observer (econometrician) but not to the investors. Blume, Easley and O'Hara (1994), on the other hand, introduce a model with asymmetric information where the volume may provide information about expected future returns to investors as well. In this study we shall demonstrate that cross-listed securities provide us with a unique setup to study the role of volume in the stock return dynamics.

In terms of methodology we model the joint distribution of an ADR and the corresponding ordinary share returns as a bivariate Vector Error Correction (VEC)-GARCH process with skewed Student-t innovations (Hansen, (1994)). Such a model suits our purposes well and is also shown to perform well when applying diagnostic tests. Within this framework we study the dynamics of the mean, the variance, and the skewness spill-overs between the ADRs and their underlying Tokyo listed shares. Next, we study the role of trading volume in the conditional mean dynamics of the ordinary share and ADR returns by means of both non-parametric (White and Hong (1993)) moment- and parametric (regression based) tests.

Our key findings are as follows. First, at the return level we find that the major channel of information transmission is via cross-border trading induced by the price differential between the Tokyo and New-York closing prices. Interestingly, the adjustment mechanism exhibits some non-linear dynamics which is consistent with cross-border trading by investors facing different levels of transaction costs. We also find that the US investors tend to overreact to news from Tokyo but not vice-versa. Overall, our findings suggest that at the return level the Tokyo stock exchange emerges as the dominant market, while the US stock exchanges play a satellite role. Second, we find significant cross-market volatility spill-overs and also some limited evidence of a cross-market leverage effect. However, in contrast to a first moment (return) transmission mechanism, we find no evidence of asymmetry in volatility spill-overs. Third, we find some evidence of cross-market skewness dynamics. In particular, we find that conditional on the past history of positive pricing shocks on the Tokyo (US) stock markets, the skewness of the ADR (ordinary share) returns is forecasted to be more negative. This finding is consistent with the stochastic bubbles hypothesis, extended to a multiple markets setup. Finally, we find strong empirical evidence of the Tokyo (US) trading volume affecting the intensity of the pricing information transmission from the Tokyo to the US (US to Tokyo) stock exchanges. In particular, our findings suggest that a cross-market price differential accompanied by a high trading volume on the Tokyo (US) markets is more likely to be corrected at the opening of the US (Tokyo) stock exchanges not being transmitted to the next trading day. Curiously, the impact of the Tokyo Stock Exchange trading volume is transmitted to the subsequent trading day on the US stock markets, while the impact of the US trading volume appears to have no impact of the opening of the Tokyo stock exchange. These findings support the idea that the trading volume provides additional information to information already implicit in stock prices.

The remainder of the paper is organized as follows. In Section 3.2 we briefly review the existing literature on the cross-listed securities and price-volume relationship. Section 3.3 describes the data. In Section 3.4 we discuss the methodology used in this research. In Section 3.5 we present and discuss the estimation results. Section 3.6 concludes.

3.2 Literature Review

The majority of non-US companies cross-list their shares in the form of American Depositary Receipts (ADRs). An ADR is a negotiable certificate which indirectly represents the ownership of shares of a foreign corporation for domestic investors. The US depositary bank holds the shares in the country of origin and converts all related payments into US dollars. Each receipt denotes a specific number of shares it can be converted into according to a specified conversion rate.[1] Since an ADR and the underlying share represent the same value, a natural question is whether they share the same price generating process, and, in particular, it becomes relevant to understand the features of the information transmission mechanism of such a share, traded in a "global" market.

Trading in identical financial assets in different markets depends on various factors, such as transaction/communication costs, exchange rate risk, different timing zones, etc. At one extreme, for sufficiently high costs there will be no inter-market trading (perfectly segmented markets). On the other hand, zero transaction costs in the presence of no restrictions on the cross-market capital flows will equalize the prices of any (simultaneously) traded identical assets, eliminating any arbitrage opportunities. In this case we would say that markets are perfectly integrated (Garbade and Silber, (1979)). In reality, however, due to both different time zones and non-negligible transaction costs, international markets are more likely in the intermediate region of partial integration. In the context of cross-listed securities this means that the price adjustment does not occur immediately, giving rise to one of the following possibilities:

a) The price adjustment between two markets A and B is symmetric.

b) The magnitude of price adjustment of the security traded on market B to the information

[1] For a comprehensive survey of ADRs see Karolyi (1998).

revealed on market A is higher than the one of market A.

Situation *b*) is defined by Garbade and Silber (1979) as the "dominant-satellite markets" relationship, where market A is defined as the dominant one and B as the satellite market.

An asymmetric transmission of information has been confirmed by a number of empirical studies. Most of these studies concentrate on the return spill-overs (first moment transmission) between the markets. Neumark *et al.* (1991) study the behavior of multiple-listed US securities traded on the New York, London, and Tokyo Exchanges. Based on their findings, the New York stock exchange emerges as the dominant market for US cross-listed firms. In a more recent study Eun and Sabherwal (2003) examine the contribution of cross-listings for the price discovery for a sample of Canadian firms whose stocks are listed on both the Toronto exchange and US markets. They find that US prices adjust more to the prices on the Toronto stock exchange than vice versa. The idea of the domestic stock exchange playing the leading role in the information transmission process is supported by Hauser *et al.* (1998) and Lieberman *et al.* (1999) in their studies of multiple-listed Israeli firms, Kadapakkam and Misra (2003) for Indian GDRs listed on the London Stock Exchange, Eun and Jang (1997) for stocks cross-listed on the New-York, London and Tokyo stock exchanges, and other contributions. On the other hand, Phylaktis and Manalis (2005) in their study of stocks listed on Greek and German stock markets report the dominant role of German markets in the price discovery process.

Several studies investigate the mechanism of the information transfer between stocks listed on central and regional stock exchanges. Hasbrouck (1995) studies the dynamics of the pricing process of the Dow stocks listed on the NYSE and regional US stock exchanges. He finds that the price discovery is concentrated at the NYSE while the regional markets behave as the satellite ones, but not as pure satellites, suggesting that the price discovery process takes place on both "central" and regional stock markets. Similar results are reported by Harris *et al.* (1995).

An overall conclusion from these and other studies is that, at the return level, domestic stock markets emerge as the informationally dominant ones. Surprisingly, however, none of these studies considers the question whether this information transfer asymmetry extends to the dynamics of higher moments, such as the variance or the skewness which, undoubtedly, play an important role in financial decision making. For instance, Hong and Stein (2003) develop a model showing how skewness is related to the dispersion of information among investors. Bates (1997) interprets the conditional skewness inferred from option prices as a measure of crash expectations. Therefore, we believe that studying the dynamics of these moments will provide a much more comprehensive picture of the information transfers between markets.

A second common feature shared by these studies is that they investigate the *unconditional* dynamics of the price-discovery process, thus implicitly assuming that the intensity of the pricing information transfer is constant over time. We empirically test the validity of this assumption by studying the role of the trading volume in the cross-market information transmission dynamics. An extensive body of the literature relates the magnitude of the conditional serial correlation to lagged volume (turnover). Campbell, Grossman, and Wang (1993) study the impact of lagged volume on equity returns in a theoretical model, making a distinction between "liquidity" traders, who trade for some exogenous reasons and mean-variance utility maximizers. The latter are ready to absorb a buying/selling pressure of the "liquidity" traders in exchange for an increase in expected return, leading to a return reversal. Since a buying/selling pressure is reflected in a high number of transactions, an abnormal lagged volume increases the likelihood of observing a subsequent return reversal. Blume, Easley, and O'Hara (1994) and Wang (1994) develop theoretical models in which investors receive the signals with different quality (precision). In these models the lagged volume provides an additional information which cannot be extracted by looking at the price statistics alone.

The dynamics of the serial correlation of stock returns and the role of trading volume in the latter has also been studied by an extensive body of empirical work. Dufee (1992) studies the relation between serial correlation and trading volume using aggregate monthly data. He reports a statistically significant relationship between volume shocks and return reversals. Conrad, Hameed, and Niden (1994) examine the profitability of weekly contrarian strategies based on high/low volume filtration for the stocks listed on the US stock markets. They report that a high number of transactions is associated with return reversals in subsequent period, while a low volume is more likely to generate momentum. Bremer and Hiraki (1999) explore the serial correlation-volume dynamics of the stocks listed on the TSE. They report that loser stocks with high trading volume tend to have larger price reversals in the following week. On the contrary, Cooper (1999) reports that for large capitalization stocks a decline in volume is associated with return reversals and vice versa. A positive relationship between the magnitude of momentum and lagged turnover is also reported by Lee and Swaminnathan (2001) and Chan *et al.* (2000). Chordia and Swaminathan (2000) study the lead-lag patterns of the stocks listed on NYSE/AMEX. They find that daily and weekly returns on high volume portfolios lead returns on low volume portfolios; they explain this phenomenon by the differential speed of adjustment of high and low volume portfolios to the information in market returns.

Examining the role of the trading volume in the dynamics of the price discovery process of cross-listed stocks has a number of important advantages. First, studying the volume-return interactions for the *same* security listed on *multiple* markets is a natural generalization of the studies mentioned above. Second, cross-listed shares provide a unique opportunity to discriminate between a non-informative role of volume (that is, volume serving as a proxy) as in Campbell, Grossman, and Wang (1993), and the informative role of the former as in Wang (1994) and Blume, Easley, and O'Hara (1994). Our approach is based on a simple idea that if trading volume serves solely as a proxy then the impact of an increase of the Tokyo trading volume on the subsequent return of the ADR in New York and the impact of an increase of the New York trading volume on the subsequent return of the ordinary share should be symmetric since we are dealing with the same security listed on different trading locations. This will not be the case if trading volume conveys an additional information to the investors.

3.3 Data Description

Our sample consists of ten Japanese corporations, whose stocks are simultaneously listed on both the New York and Tokyo stock exchanges. Each firm is a renowned corporation whose shares are actively traded on both stock markets. Names of the companies and their brief description can be found in Appendix 3.A.

In our study we use the daily opening and closing prices as well as the trading volumes on the Tokyo and New York stock exchanges. The New York opening prices are obtained from Datastream International. The New York closing prices and trading volume are obtained from the CRSP files. The Tokyo opening and closing prices and the trading volume of the ordinary shares are obtained from the Tokyo Stock Exchange (TSE) data archive.[2] The opening (10:00 AM) and closing US dollar/yen exchange rates are used to convert US prices into domestic ones (yens). This data was obtained from Datastream International and the Federal Reserve database, respectively. Our sample covers the period from January 2001 up to December 2004, giving rise (after excluding holidays) to 946 daily observations per series.

In Table 1 we present the descriptive statistics of the daily close-to-close log-returns on the ordinary shares and their yen-denominated ADRs. Most of the stocks exhibit a negative (though statistically insignificant) time drift during the sample period. Also, all the stocks are characterized by a relatively high variance. On the other hand, for most of the stocks the skewness coefficients are statistically insignificant. Based on the high estimated values of kurtosis, the null of normality is strongly rejected for all series.

[2] We thank Akiko Kamesaka and Uri Ben-Zion for kindly providing us this data.

Table 1: Descriptive statistics

	Ordinary Share				ADR						
	Mean	St.Dev.	Skew.	Kurt.	Mean	St.Dev.	Skew.	Kurt.	V	S	K
Canon	0.0003	0.022 (0.015)	0.11 (0.44)	3.67 (5.46)	0.0003	0.021 (0.012)	0.12 (0.52)	4.32 (6.07)	0.07 (0.00)	0.92 (0.84)	0.07 (0.79)
Fuji Photo	−0.0002	0.022 (0.016)	0.03 (0.18)	4.31 (4.72)	−0.0002	0.021 (0.013)	−0.16 (−0.01)	4.72 (3.44)	0.16 (0.00)	0.15 (0.36)	0.43 (0.09)
Hitachi	−0.0004	0.025 (0.017)	0.28 (0.22)	3.85 (4.26)	−0.0004	0.024 (0.012)	0.14 (0.14)	3.84 (3.94)	0.19 (0.00)	0.27 (0.62)	0.97 (0.46)
Kyocera	−0.0005	0.027 (0.019)	0.02 (0.31)	4.05 (4.49)	−0.0005	0.026 (0.014)	0.25 (0.07)	3.96 (4.36)	0.08 (0.00)	0.05 (0.36)	0.81 (0.88)
Matsushita	−0.0005	0.02 (0.015)	0.03 (0.27)	4.54 (4.23)	−0.0005	0.021 (0.013)	0.13 (0.13)	4.49 (3.77)	0.33 (0.00)	0.41 (0.48)	0.89 (0.39)
Nissan	0.0006	0.024 (0.015)	−1.36 (0.07)	19.1 (3.83)	0.0006	0.022 (0.013)	−0.9 (0.04)	11.5 (3.27)	0.05 (0.00)	0.28 (0.83)	0.16 (0.09)
Honda	0.0002	0.023 (0.015)	−1.11 (0.08)	14.2 (4.1)	0.0002	0.021 (0.011)	−0.53 (−0.02)	8.83 (6.07)	0.007 (0.00)	0.09 (0.72)	0.12 (0.18)
Sony	−0.0008	0.024 (0.014)	−0.85 (0.91)	10.1 (5.17)	−0.0008	0.023 (0.013)	−0.54 (−0.94)	7.62 (15.9)	0.83 (0.36)	0.3 (0.26)	0.15 (0.2)
TDK	−0.0004	0.03 (0.021)	0.31 (0.45)	4.51 (4.71)	−0.0004	0.027 (0.012)	0.07 (−0.04)	3.95 (4.53)	0.00 (0.00)	0.05 (0.05)	0.07 (0.83)
Toyota	0.0001	0.02 (0.014)	0.24 (0.11)	8.63 (4.49)	0.0001	0.019 (0.009)	0.07 (0.21)	7.38 (4.41)	0.16 (0.00)	0.17 (0.66)	0.17 (0.9)

The numbers without parentheses are the sample moments of the close-to-close returns

The numbers in parentheses are the sample moments of the open-to-close returns

V (S,K) denote p-values of the variance (skewness, kurtosis) equality tests for the ADR against its corresponding ordinary share. For the tests applied to the close-to-close returns the p-values are without parentheses while for the open-to-close returns the corresponding p-values are reported in parentheses.

As a preliminary comparative analysis we compare the unconditional moments, namely the variance, the skewness, and the kurtosis of the ADR and its underlying ordinary share. For each company we test the null that the coefficients of the variance (skewness, kurtosis) are equal for both the ordinary share and the ADR, and we present the resulting p-values in the last three columns, denoted by V, S, and K, respectively. In general, for the majority of companies the null hypothesis of equal skewness cannot be rejected. The same observation holds for the kurtosis, although for most of the companies the estimated values of the kurtosis are higher for the ordinary shares. On the other hand, for most of the firms the estimated variances of the ordinary share returns are higher than the ones of the corresponding ADR and for five out of ten firms this difference is also statistically significant. Noting that close-to-close returns on Tokyo and New-York overlap (see Table 2), and ,thus, part of the information from the trading on the domestic (offshore) market is potentially reflected in the prices of the ADR (ordinary share), we conduct the same analysis for the open-to-close returns which do not overlap. Sample estimates of the variance, skewness, and kurtosis of the open-to-close returns, as well as the results of the equality tests for each firm are presented in parentheses. Overall, for skewness and kurtosis the results of the equality tests remain unaltered. On the other hand, the null of equal variances is now strongly rejected for nine out of the ten companies.[3] This may be due to the fact that during a Tokyo business day trading is affected by both global and company-specific news releases, while during a trading day in New York only the first factor affects the ADR's returns.

3.4 Methodology

3.4.1 Modeling Cross-Market Moment Dynamics

In this study we adopt a fully parametric approach by modeling the joint distribution of the ADR and the underlying stock returns, an approach which will allow us to model the dynamics of the first three moments in a joint framework.

Table 2

Trading hours of TSE and New York in local times

Stock market	Tokyo time	New York time
Tokyo	9:00 am-3:00 pm	7:00 pm*-1:00 am
New York	11:30 pm.-6:00 am**	9:30 am.-4:00 pm

Notice: * denotes previous day while ** denotes the next day.

It is important to realize that while there is a considerable overlap between close-to-close returns on both markets, the trading hours of Tokyo and New York do not overlap, with the Tokyo Stock Exchange preceding the New York trading hours (see Table 2). Therefore, we

[3] In order to take into account possible effects of common currency denomination we conducted these tests with both yen and local currency denominated ADRs. The results remained virtually the same.

choose to work with open-to-close returns, which will allow us to condition sequentially the return on one market on the information revealed during the preceding trading day at the other one. To set forth notations, we shall denote by the index t the time period between 7:00 pm the evening before day t and 4:00 pm at day t by New York time, and we shall denote by the indices d and f open-to-close returns of the ordinary share and its ADR, respectively.

Specification of mean dynamics

The specification of the mechanism which governs the mean dynamics requires some elaboration. Building on the existing literature, we identify two major channels through which the information transfer might occur. The first possible channel of the information transmission is lagged return on the security from the last trading period (offshore market for Tokyo and domestic market for New York) (see Lau and Diltz (1994), Bae, Cha and Cheung (1999)), which measures the extent to which news revealed during a trading on one market is reflected in the price of the same security traded at the other market. Second, we include a "purchasing parity" (PP) correction term which is the log-difference between the last pair of closing prices on the domestic and offshore markets (see Hasbrouck (1995), Harris *et.al* (1995), Lieberman, Ben-Zion and Hauser (1999)). If the markets are efficient enough, together with negligible transaction costs, we would expect this correction term to be stationary with zero unconditional mean to exclude any long-run profits from the cross-market trading.[4]

While it may seem reasonable to assume linearity of the return spill-over mechanism, this assumption can hardly be justified in modeling the PP error correction mechanism. For the sake of simplicity, let us assume that there are only two groups of investors trading on each market: institutional investors and private traders, who face different levels of the cross-border transaction costs c_I and c_P, with $c_I < c_P$. Then, as long as the PP correction term ξ_t is smaller in absolute value than c_I, there will be no adjustment to the long-run equilibrium. On the other hand, if the deviation is large enough to exceed c_I, this will induce cross-border trading by the institutional investors, but not by the private traders. Analogously, for $|\xi_t| > c_P$ both institutional and private traders will be involved in cross-border trading. In other words, we would expect the speed of adjustment to the long-run equilibrium to be dependent on the

[4] We formally test the null of the unit root in the error correction term via Augmented Dickey-Fuller (ADF) and Phillips-Perron tests. For all the firms the null of non-stationarity has been strongly rejected suggesting that the prices on the domestic and foreign markets are cointegrated.

magnitude of the deviation from the latter, namely, on $|\xi_t|$.

Of course, this simple example is only a crude approximation to the real world. In addition to direct transaction costs, cross-border trading involves indirect costs, such as exchange rate and liquidity risks. Also, investors may vary in their attitude toward risk, implying that highly risk averse investors will be involved in cross-border trading only for $|\xi_t|$ being sufficiently high. In other words, we would expect the "portion" of PP deviation corrected at the opening of the market to be increasing in $|\xi_t|$. Consequently, we would expect the portion of the deviation corrected during the following trading day to be decreasing in $|\xi_t|$. An overall expected impact of the PP deviation on the stock (ADR) return will therefore involve a kind of trade-off between an increase in $|\xi_t|$ and decrease in the speed of adjustment, implying a sine-type curve. An alternative scenario, on the other hand, is that the portion of PP deviation corrected during the stock market opening is decreasing in $|\xi_t|$ which can be the case if, for instance, the cross-border traders wait for additional information to arrive during the following trading day. In this case the error-correction dynamics will still be non-linear, but monotonically increasing in ξ_t. Clearly, in this framework a simple linear adjustment mechanism arises as a special case.

The tests we use, as well as the empirical results of these tests, are presented in Table B.1 (see Appendix 3.B.1). For the ordinary shares only in case of four out of ten firms we are able to reject the null of a linear error correction mechanism. Also, for those firms where the null is not rejected the speed of adjustment appears to be both statistically and economically insignificant, implying that, in general, the adjustment process is likely to be completed at the opening of the Tokyo stock market. However, the results are strikingly different in case of the ADRs, where the hypothesis of a linear adjustment is strongly rejected for *all* firms, implying that the information transfer from Tokyo to New-York is not completed at the opening of the US stock market and that the adjustment to the long-run equilibrium occurs in a non-linear fashion.

Based on these findings we propose to model the mean dynamics using the following VEC-VARMA setup:

$$\text{Tokyo: } \mu_{d,t} = \mu_d + \psi_{d,t}\xi_{d,t-1} + \sum_{i=1}^{M_1}\varphi_{d,i}r_{d,t-i} + \sum_{i=1}^{M_2}\widetilde{\varphi}_{d,i}r_{f,t-i} + \sum_{i=1}^{M_3}\theta_{d,i}\epsilon_{d,t-i} + \sum_{i=1}^{M_4}\widetilde{\theta}_{d,i}\epsilon_{f,t-i}$$

$$\xi_{d,t} = p_{f,t} - p_{d,t}$$

$$\epsilon_{d,t} = r_{d,t} - \mu_{d,t}$$

$$\psi_{d,t} = \psi_{d,1} + \psi_{d,2} \left|\xi_{d,t-1}\right|$$

$$\text{New-York: } \mu_{f,t} = \mu_d + \psi_{f,t}\xi_{f,t} + \sum_{i=1}^{N_1} \varphi_{f,i} r_{f,t-i} + \sum_{i=0}^{N_2} \widetilde{\varphi}_{f,i} r_{d,t} + \sum_{i=1}^{N_3} \theta_{f,i}\epsilon_{f,t-i} + \sum_{i=1}^{N_4} \widetilde{\theta}_{f,i}\epsilon_{d,t-i}$$

$$\xi_{f,t} = p_{d,t} - p_{f,t-1}$$

$$\epsilon_{f,t} = r_{f,t} - \mu_{f,t}$$

$$\psi_{f,t} = \psi_{f,1} + \psi_{f,2} \left|\xi_{f,t}\right|$$

where $r_{d,t}$ ($r_{f,t}$) are the (open-to-close) log-returns on the ordinary share (ADR) and $p_{d,t}(p_{f,t})$ are the logs of closing prices for the ordinary share (ADR). The magnitude of the PP adjustment coefficients (ψ-s) depends on the magnitude of the deviation from the long-run equilibrium. We expect ψ_1 and ψ_2 to be significantly positive and negative, respectively, in case of scenario 1, or both significantly positive in case of scenario 2. In addition, we allow the expected returns of the ordinary share (ADR) to be dependent on its own lagged innovations as well as on the lagged innovations of the offshore (domestic) market via θ and $\widetilde{\theta}$. We also allow for the autoregressive dynamics and the cross-market spill-overs which are measured by the φ and $\widetilde{\varphi}$ coefficients. This specification seems flexible enough to capture the relevant patterns of the transmission of pricing information between the markets. The choice of the lag-order for M_1, M_2 and N_1, N_2 is based on controlling for the serial and cross-autocorrelation of returns, while the choice of M_3, M_4 and N_3, N_4 is based on controlling for the cross-and-serial correlation of the estimated residuals.

Specification of the volatility dynamics

GARCH-type models have been proven to be quite successful in capturing the clustering nature of volatility (Bollerslev, Chou, and Kroner (1992), Andersen and Bollerslev (1998)). Also, multivariate GARCH models provide a flexible framework for studying the volatility spill-over mechanism between markets (see Karolyi (1995) and Kearney and Patton (2000), among others). Thus, the following specification of the volatility dynamics is assumed

$$\text{Tokyo: } \log(h_{d,t}) = \omega_d + \alpha_d \left|z_{d,t-1}\right| + \beta_d \log(h_{d,t-1}) + \gamma_d \left|z_{f,t-1}\right| + \gamma_d^- z_{f,t-1}$$

$$\text{New-York: } \log(h_{f,t}) = \omega_f + \alpha_f \left|z_{f,t-1}\right| + \beta_f \log(h_{f,t-1}) + \gamma_f \left|z_{d,t}\right| + \gamma_f^- z_{d,t}$$

where $z_{d,t}(z_{f,t})$ are the standardized innovations defined as $\epsilon_{d,t}/h_{d,t}^{0.5}$ and $\epsilon_{f,t}/h_{f,t}^{0.5}$, respectively. Here, we assume a simple EGARCH(1,1)-type structure adjusted to the fact that trading occurs sequentially and not simultaneously. The intensity of the cross-market volatility spill-overs is measured by the coefficients γ and γ^-, where the latter measures the intensity of the cross-market leverage effect. An important advantage of an EGARCH-model is that, in contrast to the standard linear GARCH models, no restrictions on the coefficients are required to keep the volatility estimates in a positive range and, thus, no *a priori* assumptions about the sign of the spill-over effects have to be made.

Specification of skewness dynamics and conditional distribution

In contrast to an extensive body of academic literature on modeling the dynamics of the conditional variance, the literature studying the dynamics of higher order moments, and, in particular, the dynamics of the conditional skewness is quite sparse. Hansen (1994) studies the higher moment dynamics of the weekly Dollar/Swiss Franc exchange rate. He reports an inverse relationship between the skewness and the variance of the exchange rate. In a more recent study Harvey and Siddique (2000) find that when past stock returns have been high, skewness is forecasted to become more negative. A similar result is reported by Chen, Hong, and Stein (2001), who study the skewness dynamics of the individual stocks in a cross-sectional setting, and Hueng and McDonald (2005), who apply a time-series approach to aggregate stock market data. Hueng and McDonald (2005) also report positive and significant effect of the conditional variance on skewness. Jondeau and Rockinger (2003) study the higher moment dynamics of the major stock markets and report a substantial degree of persistence in the dymanics of conditional skewness. Therefore, it is important to conduct some preliminary analysis of the skewness dynamics, before we impose any structural form on the latter.

Based on our preliminary analysis, we were not able to detect any persistence in the skewness parameter for the stocks included in our sample (see Appendix 3.B.2 for the description of the tests). This suggests that if the skewness parameter is time varying, this can be due to the cross-market skewness spill-overs.

To complete the specification of the model we have to make an assumption about the distribution of the standardized innovations. A number of flexible distributions allowing for conditional asymmetry has been used in the literature (see Hansen *et al.*, 2002) for a survey). Here, we assume that the standardized innovations z's follow a skewed Student-t distribution (Hansen, 1994) with a time-varying parameter $\lambda \in (-1, 1)$ which determines the shape of the distribution function.[5] For $\lambda > 0$ the mode of the density is to the left of zero and the variable is skewed to the right, and vice-versa, when $\lambda < 0$.

$$z_{d,t} \sim ST(\lambda_{d,t}, \eta_d)$$

$$z_{f,t} \sim ST(\lambda_{f,t}, \eta_f)$$

We assume the following motion law for the shape-parameter for each market

$$\text{Tokyo: } w_{d,t} = \delta_{1,d} + \delta_{2,d} \sum_{i=t-1}^{t-10} I^r_{f,i} + \delta_{3,d} \sum_{i=t-1}^{t-10} I^v_{f,i}$$

$$\lambda_{d,t} = -1 + \frac{2}{1 + \exp(w_{d,t})}$$

$$\text{New-York : } w_{f,t} = \delta_{1,f} + \delta_{2,f} \sum_{i=t}^{t-9} I^r_{d,i} + \delta_{3,f} \sum_{i=t}^{t-9} I^v_{d,i}$$

$$\lambda_{f,t} = -1 + \frac{2}{1 + \exp(w_{f,t})}$$

where $I^r_{d,t}(I^r_{f,t})$ is the indicator function taking the value 1 if $\epsilon_{d,t}(\epsilon_{d,t}) > 0$, $I^v_{d,t}(I^v_{f,t})$ is the indicator function taking the value 1 if $\epsilon^2_{d,t} > h_{d,t}$ $(\epsilon^2_{f,t} > h_{f,t})$, and the transformation $-1 + \frac{2}{1+\exp(x)}$ is applied to keep the shape parameter in the $(-1, 1)$ range. Here we allow for two possible channels of cross-market dynamics with asymmetry. The first one is via the past history of pricing shocks on the offshore market (for Tokyo) and the domestic market (for New-York), which is measured by δ_2. One of the possible explanations of how the asymmetry in the stock

[5] A brief review of Hansen's Student-t distribution is provided in Appendix 3.C. This density function has been used by Jondeau and Rockinger (2003) and Hueng and McDonald (2005) in their studies of higher moment dynamics in stock and foreign exchange markets.

returns can be related to the past history of the latter comes from the stochastic bubble models pioneered by Blanchard and Watson (1982), where the asymmetry is due to the popping of the bubble. Here the past history of pricing shocks comes to measure whether there has been a "momentum" in stock returns which usually precedes the bursting of a bubble during the last two trading weeks. Based on this theory we would expect δ_2 to be significantly positive. The second channel is via an increase in the volatility of the stock return, which is measured by the deviation of ϵ^2 from its expected value, namely h_t and allows for the possible effect of the volatility on skewness, as reported by Hueng and McDonald (2005).

3.4.2 Investigating Return-Volume Dynamics

Define by v_d and v_f the levels of the trading volume on the Tokyo and the US stock markets, respectively. We are interested in understanding the role of the trading volume in the price generating process of the cross-listed securities. The issue of particular interest is the role of the trading volume in the mean dynamics of the stock returns. On the one hand, studying the role of the trading volume in the price discovery process provides us important clues for understanding the dynamics of the convergence of stock price towards its fundamental value. On the other hand, studying the ability of the trading volume to predict future stock returns may also be of interest for practitioners. Thus, the following hypothesis are tested

$$E(r_{d,t} \left| \xi_{d,t-1}, r_{f,t-1}, v_{f,t-1} \right.) = E(r_{d,t} \left| \xi_{d,t-1}, r_{f,t-1} \right.)$$

$$E(r_{f,t} \left| \xi_{f,t}, r_{d,t}, v_{d,t} \right.) = E(r_{f,t} \left| \xi_{d,t-1}, r_{f,t-1} \right.)$$

The first hypothesis states that conditional on the past ADR return $r_{f,t-1}$ and the error correction term $\xi_{d,t-1}$, the return on the domestic stock is mean independent from the trading volume on the foreign market. Under the second hypothesis, conditional on the stock return on domestic market $r_{d,t}$ and the error correction term $\xi_{f,t}$, the trading volume on the domestic market plays no role in the mean dynamics of the return on the ADR.

A nonparametric approach seems to be an appropriate starting point in order to reduce the probability of rejecting the null due to incorrect parametric assumptions. There exist various nonparametric approaches to test the abovementioned hypothesis. Some tests involve estimation of the conditional means both under the null and the alternative, while other test for the omitted variable, and, in general, require the estimation of the mean under the null only. Taking into account the "curse of dimensionality" we choose to proceed with an omitted variable-type test. More specifically, let y be the variable of interest and let x be the explanatory (conditioning) variable. Also, let z be a potentially omitted variable. Finally, let $f(x)$ be the expectation of y conditional on x. The following M-test is considered

$$E\left\{(y - f(x)) \cdot z\right\} = 0$$

The mean independence of y from z conditional on x implies that the deviations of y from its conditional mean $f(x)$ will also be uncorrelated with z. Therefore, this test can be viewed as a nonparametric moment test. Define by $\hat{M}$ the sample analogue of $E\left\{(y - f(x)) \cdot z\right\}$. Our testing procedure is based on the following statistic, satisfying under the null hypothesis

$$\sqrt{n}\hat{M} \overset{ass}{\to} N(0, V\left\{(y - f(x))\left(z - E(z\,|x\,)\right\}\right).$$

The test statistic and its limit distribution under the null are derived by White and Hong (1993). By replacing $V(\cdot)$ by its sample analogue, this statistic can easily be calculated. It is also reported to perform well in simulation studies (see Euwals, Melenberg, and Van Soest (1998)). Since most of the studies reviewed suggest that the trading volume affects the return dynamics via auto (cross) correlation, it seems reasonable to test whether the return-volume interaction term should be included in the specification of the conditional mean. Therefore, for the ordinary share we define $y = r_{d,t}$, $x = (r_{f,t-1}, \xi_{d,t-1})$, and $z = (r_{f,t-1} \cdot v_{f,t-1}, \xi_{d,t-1} \cdot v_{f,t-1})$ and for the ADR $y = r_{f,t}$, $x = (r_{d,t}, \xi_{f,t})$ and $z = (r_{d,t} \cdot v_{d,t}, \xi_{f,t} \cdot v_{d,t})$. In other words, for each market we consider two M-tests. The reason for splitting the test into two parts is twofold. First, the trading volume can potentially play a role in either the return spillover or the error correction dynamics or in both of them. Second, by splitting the test we reduce the dimension of the non-parametric estimate and thus reduce the "curse of the dimensionality" problem.

Calculation of test statistic requires non-parametric estimates of $f(x)$ and $E(z\,|x)$ implying that the results of the test are potentially sensitive to the choice of bandwidth. To take this potential sensitivity into account we adopt the following strategy. First, for each test we choose the bandwidth for $f(x)$ and $E(z\,|x)$ based on cross-validation[6]. Then we calculate the value of the statistic both for the "optimal" (cross-validated) values of the bandwidth and for its fractions. As a result, for each test we obtain a series of test statistics $\frac{n\hat{M}^2}{\hat{V}}$ where each of them has a $\chi^2(1)$ distribution under the null. We base our inference on the following rule. If all statistics exceed the critical value of a $\chi^2(1)$ distribution then the null is rejected. If all statistics are below the $\chi^2(1)$ critical value, then we do not reject the null. Otherwise, we look at the maximum value of the test statistics and compare it to the "pseudo" critical value from the Bonferonni inequality.[7] If the maximum test statistic exceeds the "pseudo" critical value, the null is rejected as well. In all other cases, we consider the results as inconclusive.

In order to assess the robustness of our results and also to get some further insights into the return-volume dynamics we also test the null parametrically. More specifically, for each firm we estimate the following two regressions

$$\text{1) Tokyo:} r_{d,t} = \mu_d + \psi_{d,t}\xi_{d,t-1} + \widetilde{\varphi}_{d,t}r_{f,t-i} + \epsilon_{d,t}$$

$$\psi_{d,t} = \psi_{d,1} + \psi_{d,2}\left|\xi_{d,t-1}\right| + \psi_{d,3}\widetilde{v}_{f,t-1} + \psi_{d,4}\widetilde{v}_{d,t-1}$$

$$\widetilde{\varphi}_{d,t} = \varphi_{d,1} + \varphi_{d,2}\widetilde{v}_{f,t-1}$$

$$\text{2) New-York: } r_{f,t} = \mu_f + \psi_{f,t}\xi_{f,t} + \widetilde{\varphi}_{f,t}r_{d,t} + \epsilon_{f,t}$$

$$\psi_{f,t} = \psi_{f,1} + \psi_{f,2}\left|\xi_{f,t}\right| + \psi_{f,3}\widetilde{v}_{d,t} + \psi_{f,4}\widetilde{v}_{f,t-1}$$

$$\widetilde{\varphi}_{f,t} = \varphi_{f,1} + \varphi_{f,2}\widetilde{v}_{d,t}$$

where $\widetilde{v}$ denotes the normalized trading volume (that is, the demeaned volume scaled by its estimated standard deviation).[8] The reason for the normalization is that for all firms trading

[6] Throughout this paper we use a Gaussian kernel.

[7] Using Bonferonni inequality as the upper bound for obtaining critical values is not new. For instance, it is used by Foster, Smith and Whaley (1997) in their study of the distribution of the maximal R^2

[8] We use the total number of shares of a specific firm traded on a particular trading day on the Tokyo (US) stock markets (adjusted to the conversion rate) as a measure of the trading activity. The same measure has been used by Andersen (1996), Bremer and Hiraki (1999), Gervais, Kaniel, and Mingelgrin (2001), and others. An alternative widely used measure is the individual *turnover* which is defined as the number of shares traded divided by the number of shares outstanding. As a common practice this measure is used to reduce the low-

is concentrated on the domestic market and, therefore, in order to compare the magnitude of the volume effect it seems appropriate to measure the trading activity on both markets using a common measurement scale. We allow the trading volume to affect the intensity of the cross-market information transfer via the return spill-over (measured by φ_2) and through the error correction mechanism (measured by ψ_3). The null of no cross-market volume effects can be tested by looking at the significance of φ_2 and ψ_3 individually as well as by testing the null $\varphi_2 = \psi_3 = 0$. In addition, since the price differential ξ is related to the trading on both domestic and foreign markets we also let the intensity of the error correction to be dependent on the lagged trading volume on the TSE (for the ordinary share) and on the US markets (for the ADR) via the coefficient ψ_4.

3.5 Empirical Results

In this section we present and discuss our empirical findings. First, we present the estimates of the cross-market moment dynamics estimated within a bivariate skewed Student-t model framework, as described in the subsection 3.4.1. Next, we present our findings on the trading volume-mean return dynamics in the subsection 3.5.2.

3.5.1 Cross-Market Moment Dynamics

In Table 3.A. we present the estimates of the conditional mean equations of the ordinary shares and the ADRs. In case of the ordinary share only four out of ten stocks exhibit statistically significant cross-market information spillover which mainly occurs via the adjustment of the PP deviation, while, in general, the return spillover coefficients ($\widetilde{\varphi}$'s) are both statistically and economically insignificant. These findings support the results of our preliminary analysis by indicating that the information transmission at the return level is completed at the opening of the Tokyo stock exchange.

On the other hand, in case of the ADRs the estimates of the conditional mean dynamics

frequency variations in the data (Campbell, Grossman, and Wang (1993)) or to control for the size effect (Lee and Swaminathan (2000)). Obviously, the size effect is not the issue to be concerned about in our setup, since we are dealing with the same firm and with the same underlying market value for both the ordinary share and the ADR. Also, due to our relatively small (in a "long-run" terms) sample we believe that the impact of the low-frequency events is of low magnitude.

exhibit a strikingly different pattern. For all companies the coefficients of the PP correction term are positive and both statistically and economically significant. Also, for all the firms a non-linear term of the PP adjustment has a negative sign and is statistically significant for eight out of ten companies in the sample, which is consistent with our cross-border trading costs hypothesis. Similar to the ordinary shares, the coefficients of the (contemporaneous) cross-market return spill-overs, in general, are statistically insignificant, suggesting that, for both the Tokyo and the US market, cross-border trading induced by the cross-market price differential appears to be the major channel of the information transmission at the return level. However, the information revealed during the trading day on the Tokyo stock exchange is not fully reflected in the opening prices of the ADRs, having a highly significant impact during the trading day on the US markets. Consistent with other studies, these findings suggest that the price discovery process is concentrated at the domestic (Tokyo) stock market.

While, in general, we find no evidence of contemporaneous cross-market return spillovers, the coefficients of the lagged return spill-overs, namely the $\tilde{\varphi}_i$-s (for $i > 1$) and the $\widetilde{\theta}$-s provide an additional insight into the dynamics of the information transfer between the markets. While being statistically insignificant in case of the ordinary shares, these coefficients are significantly negative for most of the ADRs, suggesting that not only the news from Tokyo has an impact during the trading day in New-York but also that the US investors systematically *overreact* to the latter. Overall, these findings suggest that at the return level the Tokyo stock market emerges as the dominant one while the US market appears to play a satellite role in the information transmission mechanism. However, this may not necessarily be the case for the higher moment spill-overs. Thus, we turn now to the analysis of the variance and skewness dynamics.

In Table 3.B. we present the estimates of the variance equations. For all the firms we find statistically significant volatility spill-overs both from the Tokyo to the US markets and vice versa. Also, for five out of ten companies in our sample we find that the volatility of the ordinary share (ADR) return is negatively correlated with the lagged return innovations from the offshore (domestic) markets, a finding which can be attributed to the cross-market leverage effect. Curiously, this effect appears to be much more pronounced for the shares traded on the Tokyo exchange than for the ADRs. When one compares the intensity of the cross-market volatility spill-overs, this effect has to be taken into account, since the intensity is sign dependent. Thus, we base our comparison by testing the following hypothesis

$$H_0\colon\ \gamma_d + \gamma_d^- I_{L,d} = \gamma_f + \gamma_f^- I_{L,f}$$

where $I_{L,d}$ ($I_{L,f}$) takes the value 1 if $\gamma_d^-(\gamma_f^-)$ are statistically significant, and zero otherwise. The resulting p-values are reported in the $+(-)$ labeled row, where $+(-)$ denotes the test for asymmetric spillovers which does not (does) take into account the leverage effect, respectively. The results clearly indicate that, in general, the null of symmetric volatility spillovers cannot be rejected for most of the firms at any legitimate size level. This comes in sharp contrast with the findings of Xu and Fung (2002) who study the mean/variance dynamics of the China-backed stocks listed on the Hong-Kong and New-York stock exchanges. They report that the stocks listed on the offshore market (namely, New-York) play a bigger role in the volatility spillover process than those listed on the domestic one. This can be due to the fact that the Hong-Kong monetary policy closely follows the US Federal Reserve interest rate movements to avoid interest rate arbitrage (Xu and Fung (2002)), which makes the Hong-Kong stock market sensitive to any macroeconomic news released during the trading day in New-York. Also, numerous studies indicate that the US market plays a major role in the information transmission to the national stock markets in general, and to emerging markets in particular. The Tokyo stock exchange, on the other hand, is a developed market which is also relatively isolated from the US stock market compared to other developed and emerging markets (see, for instance, Berben and Jansen (2005)).

In Table 3.C. we report the estimates of the skewness/kurtosis dynamics. For four out of ten firms in the sample we find strong empirical evidence of cross-market dynamics in the shape parameter which governs the asymmetry of the distribution of the returns. More specifically, we find that conditional on the past history of positive pricing shocks on the foreign (domestic) markets, the distribution of the ordinary share (ADRs) returns becomes more negatively skewed, which is consistent with the dynamics predicted by the stochastic bubble models. Thus, we complement and extend the results reported by Harvey and Siddique (2000) to our multiple markets setup. On the other hand, in contrast to the findings of Hueng and McDonald (2005) we find no evidence that skewness is changing during the turbulent periods. The results remain unaltered for different specifications of the turbulent periods.[9] The most natural explanation of this contradiction comes from the fact that Hueng and McDonald (2005) study the conditional distribution of stock market indices. The skewness of a stock market index portfolio, like every portfolio, can be decomposed into a skewness term of the individual assets and the coskewness terms, namely the dependence structure between the returns of the individual stocks. Numerous papers report shifts in the dependence structure of the stock returns during the periods of high market turbulence (see Longin and Solnik (1995), Ramchand and Susmel (1998), Edwards and Susmel (2001), among others). Thus, shifts in the skewness of the stock market returns are potentially attributable to the shifts in the interdependence structure of the individual assets. These shifts in conjunction with the clustering nature of the stock returns volatility can also explain the high persistence of the skewness reported by Jondeau and Rockinger (2003).

Since the specification of the conditional distribution function plays an important role in this research, we conduct a number of diagnostic tests. The results are presented in Table 4. The Ljung-Box test applied to the normalized and normalized squared innovations, in general, fails to detect significant autocorrelations, suggesting that the conditional mean/variance specifications capture the dynamics of the information transfer reasonably well. As an overall test we study the distribution of the probability integral transforms, which, under the null of correct specification, follows an i.i.d $U(0,1)$ distribution (Diebold *et al.* (1998)). High p- values of the Kolmogorov-Smirnov (K-S) test indicate that the null of i.i.d $U(0,1)$ distribution cannot be rejected at any reasonable size level. Also, the plots of the empirical distribution of the integral transforms are all very close to the one implied by the uniform distribution, a finding which in conjunction with high p-values of the BDS test applied to the integral transforms supports the results of the K-S test[10]. Based on these results we conclude that our model appears to be an appropriate framework for studying the dynamics of the pricing information transfer.

Up to this point we did not consider the impact of any conditional variable other than the error correction itself on a price discovery process. As dicussed in Section 3.2 one of the variables which potentially can effect the dynamics of the price discovery process is the trading

[9] Among different variants of this model we replaced the counting "turbulence" function by the conditional cross-market variance, its own lagged variance, and also tried a counting function with different lag lengths. The results remained qualitatively the same.

[10] The data required to reproduce these results is available from the authors upon request.

volume. The role of the trading volume in the price discovery process will be the focus of the following subsection.

Table 3.A. : Conditional mean dynamics

Ordinary Share -TSE

	Canon	Fuji	Hitachi	Kyocera	Matsushita
μ	-0.0001 (0.0003)	-0.0015^{**} (0.0005)	-0.0002 (0.0005)	-0.0007 (0.0006)	-0.0014 (0.0005)
ψ_1	0.039 (0.084)	-0.118 (0.102)	-0.123 (0.105)	-0.161 (0.115)	-0.055 (0.093)
ψ_2	0.0066 (3.496)	11.65^{**} (4.83)	0.673 (4.51)	9.79^{**} (3.78)	2.29 (4.003)
$\tilde{\varphi}_1$	-0.036 (0.057)	-0.083^{*} (0.044)	0.015 (0.063)	0.136 (0.215)	-0.008 (0.048)
$\tilde{\varphi}_2$		-0.06 (0.037)			
φ_1					-0.0073 (0.034)
$\tilde{\theta}_1$				-0.24 (0.225)	

Tokyo: $\mu_{d,t}= \mu_d+\psi_{d,t}\xi_{d,t-1}+ \sum_{i=1}^{M_1} \varphi_{d,i}r_{d,t-i}+ \sum_{i=1}^{M_2} \widetilde{\varphi}_{d,i}r_{f,t-i}+ \sum_{i=1}^{M_3} \theta_{d,i}\epsilon_{d,t-i}+ \sum_{i=1}^{M_4} \widetilde{\theta}_{d,i}\epsilon_{f,t-i}$

New-York: $\mu_{f,t}= \mu_d+\psi_{f,t}\xi_{f,t}+ \sum_{i=1}^{N_1} \varphi_{f,i}r_{f,t-i}+ \sum_{i=0}^{N_2} \widetilde{\varphi}_{f,i}r_{d,t}+ \sum_{i=1}^{N_3} \theta_{f,i}\epsilon_{f,t-i}+ \sum_{i=1}^{N_4} \widetilde{\theta}_{f,i}\epsilon_{d,t-i}$

$r_{d,t}$ and $r_{f,t}$ are returns on the domestic (Tokyo) and foreign (US) markets

$\xi_{d,t} = p_{f,t} - p_{d,t}$ and $\xi_{f,t} = p_{d,t} - p_{f,t-1}$ are the cross-market price differentials

$\psi_{d,t} = \psi_{d,1} + \psi_{d,2} \left|\xi_{d,t-1}\right|$ and $\psi_{f,t} = \psi_{f,1} + \psi_{f,2} \left|\xi_{f,t}\right|$ are the time-varying speed of adjustment parameters, $\epsilon_{d,t}$ and $\epsilon_{f,t}$ are return innovations on the Japanese and US stock markets, respectively. $^{*(**)}$ denote significance at 10 (5)%

Table 3.A *(continued)* **: Conditional mean dynamics**

	ADR - NYSE (NASDAQ)				
	Canon	Fuji	Hitachi	Kuocera	Matsushita
μ	0.0015^{**} (0.0003)	0.0009^{**} (0.0004)	0.0025^{**} (0.0004)	0.0013^{**} (0.0004)	0.0003 (0.0004)
ψ_1	0.211^{**} (0.045)	0.287^{**} (0.047)	0.146^{**} (0.042)	0.176^{**} (0.046)	0.191^{**} (0.05)
ψ_2	-2.41^{**} (0.99)	-1.78^{**} (0.73)	-1.38 (0.88)	-2.51^{**} (0.83)	-3.25^{**} (1.01)
$\tilde{\varphi}_1$	-0.053 (0.041)	-0.05 (0.045)	0.055 (0.035)	-0.011 (0.039)	0.108^{**} (0.043)
$\tilde{\varphi}_2$					-0.073^{**} (0.005)
$\tilde{\varphi}_3$					-0.064^{**} (0.027)
$\tilde{\varphi}_4$					-0.045^{*} (0.027)
φ_1	-0.073^{**} (0.03)				
$\tilde{\theta}_1$	-0.078^{**} (0.025)	-0.062^{**} (0.028)	-0.057^{**} (0.022)	-0.068^{**} (0.024)	
$\tilde{\theta}_2$			-0.031 (0.022)	-0.034 (0.024)	
$\tilde{\theta}_3$			-0.046^{*} (0.024)	-0.073^{**} (0.024)	
θ_1		0.108^{**} (0.035)	0.051 (0.033)		0.055^{*} (0.032)

Tokyo: $\mu_{d,t}= \mu_d+\psi_{d,t}\xi_{d,t-1}+ \sum_{i=1}^{M_1} \varphi_{d,i}r_{d,t-i}+ \sum_{i=1}^{M_2} \widetilde{\varphi}_{d,i}r_{f,t-i}+ \sum_{i=1}^{M_3} \theta_{d,i}\epsilon_{d,t-i}+ \sum_{i=1}^{M_4} \widetilde{\theta}_{d,i}\epsilon_{f,t-i}$

New-York: $\mu_{f,t}= \mu_d+\psi_{f,t}\xi_{f,t}+ \sum_{i=1}^{N_1} \varphi_{f,i}r_{f,t-i}+ \sum_{i=0}^{N_2} \widetilde{\varphi}_{f,i}r_{d,t}+ \sum_{i=1}^{N_3} \theta_{f,i}\epsilon_{f,t-i}+ \sum_{i=1}^{N_4} \widetilde{\theta}_{f,i}\epsilon_{d,t-i}$

$r_{d,t}$ and $r_{f,t}$ are returns on the domestic (Tokyo) and foreign (US) markets

$\xi_{d,t} = p_{f,t} - p_{d,t}$ and $\xi_{f,t} = p_{d,t} - p_{f,t-1}$ are the cross-market price differentials

$\psi_{d,t} = \psi_{d,1} + \psi_{d,2} \left|\xi_{d,t-1}\right|$ and $\psi_{f,t} = \psi_{f,1} + \psi_{f,2} \left|\xi_{f,t}\right|$ are the time-varying speed of adjustment parameters, $\epsilon_{d,t}$ and $\epsilon_{f,t}$ are return innovations on the Japanese and US stock markets, respectively. $^{*(**)}$ denote significance at 10 (5)%

Table 3.A *(continued)* **: Conditional mean dynamics**

Ordinary Share -TSE

	Nissan	Honda	Sony	TDK	Toyota
μ	-0.0005 (0.00047)	-0.0004 (0.0005)	-0.0012^{**} (0.0004)	0.0003 (0.0006)	-0.00015 (0.0004)
ψ_1	0.029 (0.085)	0.245^{**} (0.093)	0.134^{*} (0.07)	-0.077 (0.108)	-0.08 (0.06)
ψ_2	1.54 (3.45)	-6.81^{**} (3.22)	-1.09 (1.33)	2.13 (3.157)	1.04 (5.11)
$\tilde{\varphi}_1$	-0.052 (0.044)	-0.07 (0.18)	-0.054 (0.058)	-0.032 (0.086)	-0.008 (0.048)
$\tilde{\varphi}_2$					
φ_1				-0.09^{**} (0.037)	-0.0073 (0.034)
$\tilde{\theta}_1$		-0.06 (0.185)			

Tokyo: $\mu_{d,t}= \mu_d+\psi_{d,t}\xi_{d,t-1}+ \sum_{i=1}^{M_1} \varphi_{d,i}r_{d,t-i}+ \sum_{i=1}^{M_2} \widetilde{\varphi}_{d,i}r_{f,t-i}+ \sum_{i=1}^{M_3} \theta_{d,i}\epsilon_{d,t-i}+ \sum_{i=1}^{M_4} \widetilde{\theta}_{d,i}\epsilon_{f,t-i}$

New-York: $\mu_{f,t}= \mu_d+\psi_{f,t}\xi_{f,t}+ \sum_{i=1}^{N_1} \varphi_{f,i}r_{f,t-i}+ \sum_{i=0}^{N_2} \widetilde{\varphi}_{f,i}r_{d,t}+ \sum_{i=1}^{N_3} \theta_{f,i}\epsilon_{f,t-i}+ \sum_{i=1}^{N_4} \widetilde{\theta}_{f,i}\epsilon_{d,t-i}$

$r_{d,t}$ and $r_{f,t}$ are returns on the domestic (Tokyo) and foreign (US) markets

$\xi_{d,t} = p_{f,t} - p_{d,t}$ and $\xi_{f,t} = p_{d,t} - p_{f,t-1}$ are the cross-market price differentials

$\psi_{d,t} = \psi_{d,1} + \psi_{d,2}\left|\xi_{d,t-1}\right|$ and $\psi_{f,t} = \psi_{f,1} + \psi_{f,2}\left|\xi_{f,t}\right|$ are the time-varying speed of adjustment parameters, $\epsilon_{d,t}$ and $\epsilon_{f,t}$ are return innovations on the Japanese and US stock markets, respectively. $^{*(**)}$ denote significance at 10 (5)%

Table 3.A *(continued)* **: Conditional mean dynamics**					
ADR - NYSE (NASDAQ)					
	Nissan	Honda	Sony	TDK	Toyota
μ	0.0004 (0.00042)	0.00012 (0.0003)	0.0018^{**} (0.0004)	0.0013^{**} (0.00035)	0.001^{**} (0.0003)
ψ_1	0.301^{**} (0.039)	0.094^{**} (0.024)	0.127^{**} (0.042)	0.133^{**} (0.03)	0.118^{**} (0.037)
ψ_2	-1.32^{**} (0.6)	-1.51^{**} (0.42)	-2.51^{**} (0.63)	-1.207^{**} (0.47)	-0.9 (0.69)
$\tilde{\varphi}_1$	-0.024 (0.041)	0.056^{*} (0.029)	0.118^{**} (0.045)	0.079^{**} (0.026)	0.0023 (0.03)
$\tilde{\varphi}_2$					-0.075^{**} (0.021)
φ_1					
$\tilde{\theta}_1$	0.0018 (0.027)	-0.064^{**} (0.021)		-0.022 (0.016)	
$\tilde{\theta}_2$	-0.014 (0.026)			0.0011 (0.017)	
$\tilde{\theta}_3$	-0.057^{**} (0.027)			-0.028^{*} (0.016)	
$\tilde{\theta}_4$				-0.039^{**} (0.017	
θ_1	0.076^{**} (0.034)				

Tokyo: $\mu_{d,t}= \mu_d+\psi_{d,t}\xi_{d,t-1}+\sum_{i=1}^{M_1}\varphi_{d,i}r_{d,t-i}+\sum_{i=1}^{M_2}\widetilde{\varphi}_{d,i}r_{f,t-i}+\sum_{i=1}^{M_3}\theta_{d,i}\epsilon_{d,t-i}+\sum_{i=1}^{M_4}\widetilde{\theta}_{d,i}\epsilon_{f,t-i}$

New-York: $\mu_{f,t}= \mu_d+\psi_{f,t}\xi_{f,t}+\sum_{i=1}^{N_1}\varphi_{f,i}r_{f,t-i}+\sum_{i=0}^{N_2}\widetilde{\varphi}_{f,i}r_{d,t}+\sum_{i=1}^{N_3}\theta_{f,i}\epsilon_{f,t-i}+\sum_{i=1}^{N_4}\widetilde{\theta}_{f,i}\epsilon_{d,t-i}$

$r_{d,t}$ and $r_{f,t}$ are returns on the domestic (Tokyo) and foreign (US) markets

$\xi_{d,t} = p_{f,t} - p_{d,t}$ and $\xi_{f,t} = p_{d,t} - p_{f,t-1}$ are the cross-market price differentials

$\psi_{d,t} = \psi_{d,1} + \psi_{d,2}\left|\xi_{d,t-1}\right|$ and $\psi_{f,t} = \psi_{f,1} + \psi_{f,2}\left|\xi_{f,t}\right|$ are the time-varying speed of adjustment parameters, $\epsilon_{d,t}$ and $\epsilon_{f,t}$ are return innovations on the Japanese and US stock markets, respectively. $^{*(**)}$ denote significance at 10 (5)%

Table 3.B : Conditional variance dynamics

	Canon	Fuji	Hitachi	Kyocera	Matsushita
Ordinary Share - TSE					
ω	-0.335^{**} (0.096)	-0.56^{**} (0.038)	-0.112^{**} (0.03)	-0.227^{**} (0.079)	-0.429^{**} (0.159)
α	0.112^{**} (0.034)	0.141^{**} (0.029)	0.025 (0.021)	0.079^{**} (0.026)	0.098^{**} (0.034)
β	0.982^{**} (0.009)	0.955^{**} (0.0045)	0.996^{**} (0.002)	0.986^{**} (0.007)	0.967^{**} (0.015)
γ_d	0.122^{**} (0.035)	0.097^{**} (0.035)	0.075^{**} (0.017)	0.062^{**} (0.028)	0.097^{**} (0.041)
γ_d^-	-0.008 (0.001)	0.011 (0.017)	-0.02^{**} (0.008)	-0.03^{*} (0.017)	0.005 (0.012)
ADR - NYSE (NASDAQ)					
ω	-0.216^{**} (0.056)	-0.67^{**} (0.037)	-0.767^{**} (0.257)	-0.122^{**} (0.019)	-0.273^{**} (0.079)
α	0.045^{*} (0.026)	0.141^{**} (0.029)	0.09^{**} (0.039)	0.019 (0.018)	$6.8 \cdot 10^{-5}$ (0.026)
β	0.988^{**} (0.0045)	0.944^{**} (0.0037)	0.935^{**} (0.026)	0.993^{*} (0.0014)	0.979^{**} (0.067)
γ_f	0.093^{**} (0.023)	0.136^{**} (0.016)	0.144^{**} (0.039)	0.066^{**} (0.017)	0.113^{**} (0.032)
γ_f^-	0.0081 (0.0082)	-0.013 (0.019)	-0.047^{**} (0.018)	0.017 (0.014)	0.024^{**} (0.012)
$+(-)$	0.49(0.49)	0.31(0.31)	0.35(0.07)	0.15(0.04)	0.57(0.94)

Tokyo: $\log(h_{d,t}) = \omega_d + \alpha_d \left|z_{d,t-1}\right| + \beta_d \log(h_{d,t-1}) + \gamma_d \left|z_{f,t-1}\right| + \gamma_d^- z_{f,t-1}$

New-York: $\log(h_{f,t}) = \omega_f + \alpha_f \left|z_{f,t-1}\right| + \beta_f \log(h_{f,t-1}) + \gamma_f \left|z_{d,t}\right| + \gamma_f^- z_{d,t}$

To test whether volatility spillovers are asymmetric the following hypotheses are tested : $H_0 : \gamma_d = \gamma_f$ and $H_0 : \gamma_d + \gamma_d^- = \gamma_f + \gamma_f^-$. The resulting p-values are reported under $+(-)$ headings, respectively. $^{*(**)}$ indicates significance at 10 (5) %

Table 3.B *(continued)* **: Conditional variance dynamics**

	Nissan	Honda	Sony	TDK	Toyota
Ordinary Share - TSE					
ω	-0.277^{**} (0.062)	-0.357^{**} (0.096)	-0.268^{**} (0.086)	-0.275^{**} (0.082)	-0.328^{**} (0.0016)
α	0.113^{**} (0.032)	0.093^{**} (0.032)	0.109^{**} (0.031)	0.069^{**} (0.032)	0.097^{**} (0.0023)
β	0.982^{**} (0.0053)	0.972^{**} (0.0086)	0.985^{**} (0.008)	0.985^{**} (0.0074)	0.979^{**} (0.0002)
γ	0.049 (0.032)	0.06^{**} (0.029)	0.07^{**} (0.028)	0.135^{**} (0.032)	0.095^{**} (0.0007)
γ^-	-0.031^{**} (0.009)	-0.035^{**} (0.014)	-0.031^{*} (0.017)	-0.014 (0.01)	-0.017 (0.011)
ADR - NYSE (NASDAQ)					
ω	-0.179^{**} (0.053)	-0.363^{**} (0.158)	-0.278^{**} (0.094)	-0.182^{**} (0.057)	-0.161^{**} (0.0005)
α	-0.017 (0.019)	0.104^{**} (0.034)	0.065^{**} (0.029)	0.048^{*} (0.026)	-0.0027 (0.01)
β	0.985^{**} (0.0053)	0.975^{**} (0.014)	0.985^{**} (0.008)	0.99^{**} (0.004)	0.989^{**} (0.0002)
γ	0.083^{**} (0.021)	0.069^{**} (0.032)	0.129^{**} (0.032)	0.079^{**} (0.023)	0.078^{**} (0.011)
γ^-	-0.019^{**} (0.007)	-0.024 (0.017)	-0.0089 (0.011)	0.013 (0.013)	0.0038 (0.011)
$+(-)$	0.21(0.61)	0.69(0.55)	0.11(0.44)	0.14(0.14)	0.15(0.15)

Tokyo: $\log\left(h_{d,t}\right) = \omega_d + \alpha_d \left| z_{d,t-1} \right| + \beta_d \log\left(h_{d,t-1}\right) + \gamma_d \left| z_{f,t-1} \right| + \gamma_d^- z_{f,t-1}$

New-York: $\log\left(h_{f,t}\right) = \omega_f + \alpha_f \left| z_{f,t-1} \right| + \beta_f \log\left(h_{f,t-1}\right) + \gamma_f \left| z_{d,t} \right| + \gamma_f^- z_{d,t}$

To test whether volatility spillovers are asymmetric the following hypotheses are tested : $H_0 : \gamma_d = \gamma_f$ and $H_0 : \gamma_d + \gamma_d^- = \gamma_f + \gamma_f^-$. The resulting p-values are reported under $+(-)$ headings, respectively. $^{*(**)}$ indicates significance at 10 (5) %

Table 3.C : Skewness/kurtosis dynamics

Ordinary Share - TSE

	Canon	Fuji	Hitachi	Kyocera	Matsushita
δ_1	-0.445 (0.412)	-0.881^{**} (0.36)	0.093 (0.42)	0.256 (0.37)	0.34 (0.343)
δ_2	0.014 (0.06)	0.145^{**} (0.064)	-0.098 (0.071)	-0.027 (0.066)	-0.041 (0.055)
δ_3	0.071 (0.075)	0.099 (0.063)	0.068 (0.069)	-0.09 (0.068)	-0.077 (0.069)
η	20.99^{**} (10.06)	8.72^{**} (2.21)	11.82^{**} (4.72)	15.1^{**} (7.41)	10.84 (3.51)

ADR - NYSE (NASDAQ)

	Canon	Fuji	Hitachi	Kyocera	Matsushita
δ_1	-1.235^{**} (0.39)	0.545 (0.436)	-1.08^{**} (0.39)	-0.175 (0.41)	0.114 (0.376)
δ_2	0.185^{**} (0.067)	-0.067 (0.066)	0.168^{**} (0.04)	0.0016 (0.068)	-0.046 (0.055)
δ_3	0.04 (0.062)	-0.065 (0.069)	0.0075 (0.069)	0.0072 (0.069)	0.0033 (0.071)
η	14.13^{**} (6.01)	31.01 (32.35)	14.07^{**} (5.67)	16.82 (10.8)	14.6 (7.5)
log-ld	5556.25	5422.32	5363.62	5201.04	5438.16

Tokyo : $w_{d,t} = \delta_{1,d} + \delta_{2,d} \sum_{i=t-1}^{t-10} I^r_{f,i} + \delta_{3,d} \sum_{i=t-1}^{t-10} I^v_{f,i}$

Shape parameter of a Skewed-t distribution: $\lambda_{d,t} = -1 + \frac{2}{1+\exp(w_{d,t})}$

New-York: $w_{f,t} = \delta_{1,f} + \delta_{2,f} \sum_{i=t}^{t-9} I^r_{d,i} + \delta_{3,f} \sum_{i=t}^{t-9} I^v_{d,i}$

Shape parameter of a Skewed-t distribution: $\lambda_{f,t} = -1 + \frac{2}{1+\exp(w_{f,t})}$

$I^r_{d,t}(I^r_{f,t})$ is the indicator function taking the value 1 if $\epsilon_{d,t}(\epsilon_{d,t}) > 0$

$I^v_{d,t}(I^v_{f,t})$ is the indicator function taking the value 1 if $\epsilon^2_{d,t} > h_{d,t}$ $(\epsilon^2_{f,t} > h_{f,t})$

$^{*(**)}$ indicates significance at 10 (5) %

Table 3.C *(continued)* **: Skewness/kurtosis dynamics**

	Nissan	Honda	Sony	TDK	Toyota
Ordinary Share - TSE					
δ_1	-0.051 (0.332)	-0.093 (0.417)	-0.122 (0.352)	0.438 (0.398)	-0.502 (0.31)
δ_2	0.011 (0.055)	0.022 (0.058)	0.026 (0.063)	-0.072 (0.062)	0.099^{**} (0.05)
δ_3	-0.006 (0.06)	-0.013 (0.076)	-0.019 (0.069)	-0.081 (0.068)	-0.03 (0.061)
η	11.73^{**} (4.96)	14.09^{**} (6.9)	10.99^{**} (3.55)	9.86^{**} (3.55)	8.15^{**} (1.94)
ADR - NYSE (NASDAQ)					
δ_1	0.062 (0.33)	0.33 (0.323)	0.037 (0.365)	0.277 (0.376)	-0.517 (0.345)
δ_2	-0.018 (0.064)	0.0089 (0.057)	-0.072 (0.058)	-0.057 (0.071)	0.083 (0.055)
δ_3	0.0098 (0.062)	-0.093 (0.059)	0.038 (0.079)	-0.031 (0.056)	0.0055 (0.072)
η	63.8 (116.8)	8.39^{**} (2.31)	7.48^{**} (1.39)	10.04^{**} (3.33)	10.3^{**} (3.34)
log-ld	5445.21	5611.35	5576.86	5277.56	5869.64

Tokyo : $w_{d,t}= \delta_{1,d}+\delta_{2,d} \sum_{i=t-1}^{t-10} I^r_{f,i}+\delta_{3,d} \sum_{i=t-1}^{t-10} I^v_{f,i}$

Shape parameter of a Skewed-t distribution: $\lambda_{d,t} = -1 + \frac{2}{1+\exp(w_{d,t})}$

New-York: $w_{f,t}= \delta_{1,f}+\delta_{2,f} \sum_{i=t}^{t-9} I^r_{d,i}+\delta_{3,f} \sum_{i=t}^{t-9} I^v_{d,i}$

Shape parameter of a Skewed-t distribution: $\lambda_{f,t} = -1 + \frac{2}{1+\exp(w_{f,t})}$

$I^r_{d,t}(I^r_{f,t})$ is the indicator function taking the value 1 if $\epsilon_{d,t}(\epsilon_{d,t}) > 0$

$I^v_{d,t}(I^v_{f,t})$ is the indicator function taking the value 1 if $\epsilon^2_{d,t} > h_{d,t}$ $(\epsilon^2_{f,t} > h_{f,t})$

$^{*(**)}$ indicates significance at 10 (5) %

Table 4 : Diagnostic tests					
			Ordinary Share - TSE		
	Canon	Fuji	Hitachi	Kyocera	Matsushita
$LB_z(10)$	0.92	0.85	0.94	0.47	0.72
$LB_{z^2}(10)$	0.69	0.39	0.28	0.06	0.46
K-S	0.21	0.84	0.64	0.75	0.96
			ADR - NYSE (NASDAQ)		
$LB_z(10)$	0.91	0.59	0.32	0.25	0.67
$LB_{z^2}(10)$	0.98	0.95	0.57	0.11	0.14
K-S	0.75	0.55	0.93	0.94	0.81
			Ordinary Share - TSE		
	Nissan	Honda	Sony	TDK	Toyota
$LB_z(10)$	0.24	0.86	0.88	0.74	0.98
$LB_{z^2}(10)$	0.77	0.77	0.62	0.88	0.72
K-S	0.99	0.95	0.94	0.77	0.95
			ADR - NYSE (NASDAQ)		
$LB_z(10)$	0.29	0.06	0.51	0.53	0.21
$LB_{z^2}(10)$	0.36	0.42	0.1	0.77	0.08
K-S	0.99	0.96	0.87	0.94	0.97

$LB_{z(z^2)}$ denotes p-values of Ljung-Box test applied to the standardized return innovations and its' squares. K-S denote p-values of the Kolmogorov-Smirnov test of i.i.d U(0,1) applied to the probability integral transforms of the estimated density function for each ordinary share-ADR pair

3.5.2 Volume-Return Dynamics

We start with the analysis of the results of the nonparametric ommited variable tests. In the upper panel of Table 5 we present the results of White and Hong M-test applied to the open-to-close returns. For each ordinary share and for each ADR under investigation we considered two tests (as discussed in the previous section), namely Test 1 and Test 2. In case of each test we calculated nine test statistics based on the "optimal" (cross-validation based) bandwidth h^* and its fractions of $(1-\alpha)$ and $(1+\alpha)$, for α lying in the (0,1) range. For most of the cases we chose $\alpha = 0.25$.[11] For each test we present statistics with the minimum and the maximum value as $[\min, \max]$. Bonferroni "pseudo" critical values for this nine-trials based test are 6.45 and 7.69 for 10 and 5 percent size level, and the standard $\chi^2(1)$ critical values are 2.7 and 3.84, respectively.

As can be seen from Table 5, for the ordinary shares only in case of two out of ten firms we are able to reject the null that the US trading volume affects the intensity of the information transfer. For the rest of the firms, based on the low values of the test statistics, we are not able to reject the null at any reasonable size level. On the other hand, for the ADR the null is strongly rejected for eight out of ten firms in our sample. The evidence of the Japanese trading volume playing a significant role in the pricing information transmission is particularly strong, taking into account the conservative nature of the Bonferroni inequality based test. Also, in case of the ADRs the test statistic appears to be substantially sensitive to the choice of the bandwidth which justifies the use of the Bonferroni bounds.

To shed some further light on the role of the trading volume in the cross-market return spill-over mechanism, we apply the same nonparametric test to the close-to-open returns. The results are presented in the lower panel of Table 5. Not surprisingly, for all firms under investigation we find the trading volume on the TSE affecting the transfer of the pricing information from Tokyo to New-York at the opening of the US stock markets, which is consistent with the results of the results of Table 3.A. However, in case of the ordinary shares the difference between the results of the White and Hong test applied to the open-to-close and close-to-open returns is indeed striking. While for only two out of ten firms we find empirical evidence of the US trading volume affecting the dynamics of the close-to-open returns on the Tokyo stock exchange, for the close-to-open returns we find such evidence for nine out of ten companies, with Fuji being the only exception as in this case the results are inconclusive. Based on the previous estimation results the US markets clearly emerge as the satellite ones and, therefore, it is possible that the impact of the US markets' trading volume, while being significant, is completed at the

[11] In a few cases we had to "oversmooth" the cross-validation based bandwidth to prevent the kernels to reach their numerical zero boundaries.

opening of the Tokyo stock exchange, as it was found to be the case with the cross-market return spill-overs and error-correction dynamics. These findings indicate that this is indeed the case suggesting that the transmission of the pricing information is bidirectional with the trading volume playing an important role in the latter.

Next, we turn our attention to the results of the regression analysis. In Table 6 we present the results of the parametric tests based on the regressions 1) and 2) estimated by the SUR approach with open-to-close returns. We report the estimates of the coefficients of the volume-return interaction terms since they constitute the major interest of this subsection. Similar to the results of the W&H test reported in the upper panel of Table 5 in case of the ADRs, for eight out of ten companies we find empirical evidence of the Tokyo trading volume affecting the transmission of pricing information from Tokyo to New-York. Overall, for six out of ten companies the impact of the Tokyo trading volume is statistically significant, based on the results of both parametric and non-parametric tests. On the contrary, only for two firms the impact of the trading volume was found to be bidirectional, with the TSE trading volume affecting the returns of the ADR and vice versa. For most of the firms the volume-return interaction term does not appear to contribute to the cross-market return dynamics with $\hat{\psi}_2$ being statistically insignificant. On the contrary, for most of the ADRs the Tokyo trading volume is inversely related to the share of the PP deviation corrected during the subsequent trading day in New-York with $\hat{\psi}_{f,3}$ being significantly negative. One of the possible interpretations of this result is that the cross-market divergence between the price of the ADR and its underlying share is more likely to be corrected at the opening of the US market when it is accompanied by a high trading volume during the previous trading day on the TSE, a finding which is consistent with the hypothesis of the trading volume conveying additional information to the one implicit in stock prices. One can think of the stock price as a linear combination of two stochastic terms, an implicit "efficient" price which represents the "true" fundamental underlying value and the divergence from the latter induced by the bid-ask spread (see, for instance, Hasbrouck (1995)). Then, when the trading on both markets is not synchronous, the price differential between the ADR and its underlying share will convey useful information regarding the change in the "fundamental" value. When the investors are heterogeneous in terms of their private information the trading volume provides additional information to the one implicit in the cross-market price differential regarding the change in the "fundamental" value which is in line with our finding that the major impact of the trading volume on the cross-market return dynamics is via the PP error correction mechanism.

To gain additional insight into the return-volume relationship it could be useful to estimate the same regressions with the close-to-open returns. However, due to a substantial time overlap between the close-to-open return on the one market and open-to close return on the other, the SUR estimates are likely to be biased due to the endogeneity problem. A standard approach to deal with this problem is to use an instrumental variable approach instead. Since most of the regressors in our regression setup, such as the returns and the trading volumes are likely to be jointly determined, finding an appropriate set of instruments becomes quite a complicated issue. Instead, we estimate the same regression with the close-to-close returns for both markets as in Lieberman, Ben-Zion, and Hauser (1999). On the one hand, for the close-to-close returns the endogeneity problem is less likely to arise, while on the other hand, a comparison of the impact of the trading volume on the open-to-close and close-to-close returns dynamics (an overall impact) will allow us to draw some conclusions regarding the role of the former in the dynamics of the close-to-open returns.

The estimation results are presented in Table 7, where, as before, for the sake of saving space, only the estimates of the volume-return dynamics are presented. For most of the ADRs the estimates of ψ_3 which, in the close-to-close return setup measure the overall impact of the TSE trading volume on the error-correction intensity are either positive and statistically significant or positive and insignificant. The only exception is Nissan where $\hat{\psi}_3$ is negative but statistically insignificant. This comes in sharp contrast with the same estimates for the open-to-returns where the estimate of the loading on the error-correction-volume interaction term is significantly negative for most of the firms. Turning to the close-to-close return dynamics of the ordinary shares we find that for all the firms the estimates of ψ_3 are positive and also statistically significant in case of nine out of ten companies, while being statistically insignificant for the open-to-close returns. Overall, our findings suggest that for the cross-listed securities the intensity of the pricing information transfer from the domestic to the foreign (foreign to domestic) markets increases with an increase in the volume during the last trading period. Also, consistent with the dominant-satellite markets hypothesis, the impact of the US trading volume appears to be completed at the opening of the Tokyo stock exchange, while the impact of the trading volume on the TSE is not completed at the opening of the US stock markets and transmitted to the following trading day. We hypothesize that these findings support the idea that the trading volume provides additional pricing information to the investors. An alternative explanation can be the "visibility" hypothesis raised by Gervais, Kaniel, and Mingelgrin (2001) who claim that positive shocks in the trading volume make the stock more "visible", attracting new investors. While this hypothesis may explain the positive relationship between the trading volume and the intensity of the error-correction mechanism, we do not see how it might explain the cross-market asymmetry found in the volume-return dynamics. Therefore, the informative role of the trading volume seems to be a more plausible explanation.

To check the robustness of our findings we re-estimate our regression models with two alternative measures of volume. First, following Lee and Rui (2002) we use detrended volume calculated as the sample innovation from the following regression

$$v_{i,t} = \beta_0 + \beta_1 t + \beta_2 t^2 + \epsilon_{i,t}$$

for each firm under investigation and for $i = \{d, f\}$. For a number of firms in our sample the trading volume is significantly increasing over time which can be due to an increase in the total number of shares outstanding. Second, it is possible that the shocks to the trading volume rather than the trading volume itself convey additional information. There is an extant amount of evidence of the clustering nature of the trading volume and, therefore, it seems reasonable to control for its predictable component. We calculate the shocks to the trading volume as the residuals from the following regressions

$$v_{i,t} = \alpha_i + \sum_{l=1}^{N_{i,f}} \beta_{i,l} v_{f,t-l} + \sum_{l=1}^{N_{i,d}} \gamma_{i.l} v_{d,t-l} + \eta_{i,t}$$

for each firm in our sample and for $i = \{d, f\}$. For some firms in our sample the lagged trading volume on the Tokyo and US stock markets explains up to 50 percent of the total variation of the current trading volume which confirms the statistical and economic significance of the predictable component. The results remain unaltered under the three different specifications of the trading volume supporting the robustness of our findings.

3.6 Summary and Conclusions

In this research we investigate the dynamics of the pricing information transmission between the stocks of Japanese firms listed on both the Tokyo and US stock markets. Unlike previous studies, we extend our analysis beyond the investigation of the mean dynamics, by studying the cross-market volatility and skewness spill-overs. We estimate a bivariate VEC-GARCH model with skewed Student-t innovations which allows for a dynamic specification of the conditional variance and skewness. In addition, we examine the role of the trading volume in the dynamics of the pricing information transfer between the markets by means of both non-parametric and parametric tests. Our key results are as follows.

First, at the return level we find that the major channel of information transmission is via the error-correction mechanism of the cross-market price differential. Interestingly, the error-correction mechanism exhibits non-linear dynamics consistent with different levels of transaction costs faced by cross-border investors. In addition, it appears that the US investors tend to overreact to the news revealed during the trading on the Tokyo stock exchange but not vice versa. Overall, consistent with other studies, we find that the Tokyo stock market emerges as the dominant one while the US stock exchanges behave as the satellite ones.

Second, we find significant bidirectional volatility spill-overs between the ordinary shares and their ADRs. However, in contrast to the first moment dynamics, no evidence of asymmetry in the cross-market variance dynamics can be found. Also, for some stocks we find that the intensity of the volatility spill-over is sign dependent, a finding which can be attributed to the cross-market leverage effect.

Third, we find some preliminary evidence of cross-market skewness dynamics. In particular, we find that conditional on the past history of positive pricing shocks on the US (Tokyo) stock exchange, the distribution of the ordinary share (ADR) return is forecasted to be more negatively skewed, a dynamic pattern consistent with the stochastic bubbles hypothesis, thus extending the results of Harvey and Siddique (2000) to a multiple-market setup.

Finally, we find solid empirical evidence of the trading volume affecting the intensity of the pricing information transfer between the markets via the error-correction channel. More specifically, the "arbitrage" opportunity induced by the cross-market price differential is more likely to be eliminated at the opening of the US (Tokyo) stock market when the former is accompanied by a high trading volume on the Tokyo (US) stock exchange during the preceding trading day. In this particular context, our results both complement and provide an interesting extension to the findings of Chordia and Swaminathan (2000) who find that high-volume stocks adjust more rapidly to new information. Interestingly, the impact of the US trading volume appears to be completed at the opening of the Tokyo stock exchange while the impact of the Tokyo trading volume is transmitted to the following trading day on the US stock markets. This asymmetry suggests that investors tend to extract additional information from the trading volume in addition to the information present in stock prices.

Our findings suggest a number of interesting issues for further research as well. First, the asymmetry found in the mean but not in the volatility spill-overs raises the question of the determinants of the stock return variance, and, in particular, the contribution of global (macro-economic) and firm-specific news in the latter. In this context, an event study of the impact of macroeconomic and firm-specific announcements on the volatility of cross-listed securities might provide interesting insights. Second, it would be interesting to test whether the trading volume affects the intensity of the information transmission at the aggregate market level. In particular, since a high trading volume is usually associated with a high volatility, the question whether shifts in the stock market interdependence structure during turbulent periods are volatility- or volume-driven appears to be of particular importance for the analysis of potential benefits from cross-market diversification. Finally, while we find solid empirical evidence of predictability of cross-listed stock returns contradicting the notion of semi-strong market efficiency, from the practical point of view it would be interesting to test whether this predictability can be exploited to earn economically significant profits. In light of our findings, cross-market investment strategies built on the price-differential/volume filters seem to be a natural starting point.

Table 5 : White and Hong (1993) minimum/maximum statistics

Table 5.A : Open-to-close returns

	ADR		Ordinary Share	
	Test 1	Test 2	Test 1	Test 2
Canon	$[0.12, 1.75]$	$[0.06, 1.17]$	$[0.43, 0.82]$	$[0.16, 0.54]$
Fuji	$[6.51^{**}, 20.01^{**(B)}]$	$[19.53^{**}, 39.2^{**(B)}]$	$[2.62, 2.83]$	$[2.08, 2.17]$
Hitachi	$[1.32, 10.25^{**(B)}]$	$[2.4, 7.47^{*(B)}]$	$[11.48^{**}, 20.45^{**(B)}]$	$[7.49^{**}, 13.92^{**(B)}]$
Kyocera	$[0.63, 1.85]$	$[0.42, 0.48]$	$[1.69, 2.66]$	$[0.002, 0.023]$
Matsushita	$[0.006, 0.92]$	$[2.17, 7.23^{*(B)}]$	$[1.05, 1.83]$	$[0.24, 0.42]$
Nissan	$[32.01^{**}, 93.4^{**(B)}]$	$[11.6^{**}, 31.3^{**(B)}]$	$[0.24, 0.44]$	$[0.002, 0.015]$
Honda	$[0.65, 2.45]$	$[1.65, 9.53^{**(B)}]$	$[0.39, 0.52]$	$[3.2^{*}, 4.87]$
Sony	$[14.8^{**}, 34.49^{**(B)}]$	$[89.28^{**}, 91.16^{**(B)}]$	$[1.58, 2.24]$	$[0.61, 0.74]$
TDK	$[0.003, 0.39]$	$[0.045, 8.83^{**(B)}]$	$[0.056, 0.24]$	$[0.27, 0.48]$
Toyota	$[0.03, 7.15^{*(B)}]$	$[4.36^{**}, 17.55^{**}]$	$[0.24, 0.28]$	$[1.16, 1.88]$

Table 5.B : Close-to-open returns

	ADR		Ordinary Share	
	Test 1	Test 2	Test 1	Test 2
Canon	$[20.8^{**}, 97.7^{**(B)}]$	$[24.6^{**}, 46.2^{**(B)}]$	$[23.3^{**}, 79.6^{**(B)}]$	$[23.6^{**}, 67.8^{**}]$
Fuji	$[12.7^{**}, 30.6^{**(B)}]$	$[14.6^{**}, 33.5^{**(B)}]$	$[2.08, 4.16]$	$[0.36, 1.56]$
Hitachi	$[6.39^{**}, 19.03^{**(B)}]$	$[2.8^{*}, 18.01^{**(B)}]$	$[4.89^{**}, 13.46^{**(B)}]$	$[9.05^{**}, 24.8^{**(B)}]$
Kyocera	$[0.007, 1.09]$	$[8.62^{**}, 28.51^{**(B)}]$	$[22.9^{**}, 41.4^{**(B)}]$	$[6.05^{**}, 10.67^{**(B)}]$
Matsushita	$[54.32^{**}, 68.69^{**(B)}]$	$[0.37, 3.99]$	$[3.63^{*}, 7.41^{*(B)}]$	$[7.41^{**}, 15.83^{**(B)}]$
Nissan	$[56.47^{**}, 85.55^{**(B)}]$	$[13.48^{**}, 43.34^{**(B)}]$	$[1.37, 2.57]$	$[6.23^{**}, 11.8^{**(B)}]$
Honda	$[33.93^{**}, 65.09^{**(B)}]$	$[6.51^{**}, 15.04^{**(B)}]$	$[7.34^{**}, 37.8^{**(B)}]$	$[11.51^{**}, 24.6^{**(B)}]$
Sony	$[67.87^{**}, 68.89^{**(B)}]$	$[20.8^{**}, 50.45^{**(B)}]$	$[1.17, 1.59]$	$[5.34^{**}, 6.67^{*(B)}]$
TDK	$[14.75^{**}, 59.67^{**(B)}]$	$[1.53, 5.54]$	$[2.9^{*}, 6.87^{*(B)}]$	$[2.77^{*}, 13.01^{**(B)}]$
Toyota	$[8.39^{**}, 23.42^{**(B)}]$	$[1.3, 7.92^{**(B)}]$	$[8.66^{**}, 16.32^{**(B)}]$	$[3.7^{*}, 10.36^{**(B)}]$

$H_0 : E\{(y - f(x)) \cdot z\} = 0$, $^{*(B)}(^{**(B)})$ indicates 90% (95%) significance based on Bonferroni bound

Ordinary Share Test 1: $y = r_{d,t}, x = \xi_{d,t-1}, z = \xi_{d,t-1} \cdot v_{f,t-1}$; Test 2: $y = r_{d,t}, x = r_{f,t-1}, z = r_{f,t-1} \cdot v_{f,t-1}$

ADR Test 1: $y = r_{f,t}, x = \xi_{f,t}, z = \xi_{f,t} \cdot v_{d,t}$; Test 2: $y = r_{f,t}, x = r_{d,t}, z = r_{d,t} \cdot v_{d,t}$

Table 6 : Volume-return dynamics (open-to-close returns)

	Canon	Fuji	Hitachi	Kyocera	Matsushita
Ordinary Share - TSE					
φ_2	0.011 (0.074)	0.015 (0.048)	-0.088^{**} (0.044)	0.037 (0.04)	-0.024 (0.033)
ψ_3	0.037 (0.067)	0.046 (0.039)	0.034 (0.047)	0.022 (0.038)	0.02 (0.031)
ψ_4	-0.041 (0.039)	0.019 (0.037)	-0.078^{**} (0.033)	0.031 (0.033)	-0.028 (0.027)
$H_0 : \varphi_2 = \psi_3 = 0$	0.54	0.22	0.1	0.18	0.75
ADR - NYSE (NASDAQ)					
φ_2	-0.06 (0.037)	0.033 (0.035)	0.011 (0.014)	0.023 (0.025)	0.011 (0.018)
ψ_3	0.003 (0.029)	0.035 (0.026)	-0.025^{**} (0.011)	-0.027^{**} (0.014)	-0.013 (0.015)
ψ_4	-0.024 (0.021)	-0.043^{**} (0.014)	-0.0027 (0.012)	0.013 (0.012)	-0.007 (0.018)
$H_0 : \varphi_2 = \psi_3 = 0$	0.04	0.002	0.057	0.12	0.69

Tokyo regression :$r_{d,t} = \mu_d + \psi_{d,t}\xi_{d,t-1} + \widetilde{\varphi}_{d,t} r_{f,t-i} + \epsilon_{d,t}$

$$\psi_{d,t} = \psi_{d,1} + \psi_{d,2}\left|\xi_{d,t-1}\right| + \psi_{d,3}\widetilde{v}_{f,t-1} + \psi_{d,4}\widetilde{v}_{d,t-1}$$

$$\widetilde{\varphi}_{d,t} = \varphi_{d,1} + \varphi_{d,2}\widetilde{v}_{f,t-1}$$

New-York regression : $r_{f,t} = \mu_f + \psi_{f,t}\xi_{f,t} + \widetilde{\varphi}_{f,t} r_{d,t} + \epsilon_{f,t}$

$$\psi_{f,t} = \psi_{f,1} + \psi_{f,2}\left|\xi_{f,t}\right| + \psi_{f,3}\widetilde{v}_{d,t} + \psi_{f,4}\widetilde{v}_{f,t-1}$$

$$\widetilde{\varphi}_{f,t} = \varphi_{f,1} + \varphi_{f,2}\widetilde{v}_{d,t}$$

$\widetilde{v}_{d,t}(\widetilde{v}_{f,t})$ - standardized trading volume on Tokyo (New-York) market

$r_{d,t}(r_{f,t})$-open-to-close return on Tokyo (New-York) market

$^{*(**)}$ indicates significance at 10 (5) %

Table 6 *(continued)* **: Volume-return dynamics (open-to-close returns)**

	Nissan	Honda	Sony	TDK	Toyota
	Ordinary Share - TSE				
φ_2	0.031 (0.032)	-0.081^* (0.048)	-0.0004 (0.016)	0.039 (0.045)	-0.093^* (0.056)
ψ_3	-0.003 (0.04)	0.099^{**} (0.037)	0.022 (0.019)	0.0032 (0.049)	0.045 (0.047)
ψ_4	0.012 (0.031)	-0.006 (0.03)	-0.024^* (0.014)	-0.028 (0.045)	0.063^{**} (0.031)
$H_0 : \varphi_2 = \psi_3 = 0$	0.47	0.029	0.11	0.55	0.22
	ADR - NYSE (NASDAQ)				
φ_2	0.027 (0.026)	0.031 (0.019)	0.038 (0.025)	-0.002 (0.012)	0.028^* (0.016)
ψ_3	-0.024 (0.017)	-0.032^{**} (0.012)	-0.065^{**} (0.021)	-0.028^{**} (0.009)	-0.022 (0.014)
ψ_4	-0.004 (0.016)	-0.009 (0.016)	0.07^{**} (0.021)	0.005 (0.01)	-0.012 (0.015)
$H_0 : \varphi_2 = \psi_3 = 0$	0.37	0.024	0.008	0.002	0.18

Tokyo regression :$r_{d,t} = \mu_d + \psi_{d,t}\xi_{d,t-1} + \widetilde{\varphi}_{d,t} r_{f,t-i} + \epsilon_{d,t}$

$$\psi_{d,t} = \psi_{d,1} + \psi_{d,2} \left|\xi_{d,t-1}\right| + \psi_{d,3}\widetilde{v}_{f,t-1} + \psi_{d,4}\widetilde{v}_{d,t-1}$$

$$\widetilde{\varphi}_{d,t} = \varphi_{d,1} + \varphi_{d,2}\widetilde{v}_{f,t-1}$$

New-York regression : $r_{f,t} = \mu_f + \psi_{f,t}\xi_{f,t} + \widetilde{\varphi}_{f,t} r_{d,t} + \epsilon_{f,t}$

$$\psi_{f,t} = \psi_{f,1} + \psi_{f,2} \left|\xi_{f,t}\right| + \psi_{f,3}\widetilde{v}_{d,t} + \psi_{f,4}\widetilde{v}_{f,t-1}$$

$$\widetilde{\varphi}_{f,t} = \varphi_{f,1} + \varphi_{f,2}\widetilde{v}_{d,t}$$

$\widetilde{v}_{d,t}(\widetilde{v}_{f,t})$ - standardized trading volume on Tokyo (New-York) market

$r_{d,t}(r_{f,t})$-open-to-close return on Tokyo (New-York) market

$^{*(**)}$ indicates significance at 10 (5) %

Table 7 : Volume-return dynamics (close-to-close returns)

	Canon	Fuji	Hitachi	Kyocera	Matsushita
Ordinary Share - TSE					
φ_2	-0.032 (0.03)	0.01 (0.034)	-0.032 (0.022)	0.035^{**} (0.017)	-0.011 (0.024)
ψ_3	0.156^{**} (0.056)	0.105^{**} (0.041)	0.091^{*} (0.05)	0.154^{**} (0.036)	0.071^{*} (0.037)
ψ_4	-0.061 (0.051)	0.04 (0.049)	-0.039 (0.043)	-0.022 (0.042)	0.065^{*} (0.039)
$H_0 : \varphi_2 = \psi_3 = 0$	0.02	0.025	0.11	0.0000	0.093
ADR - NYSE (NASDAQ)					
φ_2	-0.097^{**} (0.028)	-0.002 (0.022)	-0.049^{**} (0.015)	-0.018 (0.015)	-0.034^{**} (0.016)
ψ_3	0.057^{*} (0.031)	0.029 (0.023)	0.056^{**} (0.016)	0.002 (0.016)	0.03 (0.019)
ψ_4	0.02 (0.021)	-0.003 (0.011)	0.014 (0.0092)	0.009 (0.01)	-0.014 (0.014)
$H_0 : \varphi_2 = \psi_3 = 0$	0.0003	0.08	0.0018	0.12	0.11

Tokyo regression : $r_{d,t} = \mu_d + \psi_{d,t}\xi_{d,t-1} + \widetilde{\varphi}_{d,t} r_{f,t-i} + \epsilon_{d,t}$

$$\psi_{d,t} = \psi_{d,1} + \psi_{d,2}\left|\xi_{d,t-1}\right| + \psi_{d,3}\widetilde{v}_{f,t-1} + \psi_{d,4}\widetilde{v}_{d,t-1}$$

$$\widetilde{\varphi}_{d,t} = \varphi_{d,1} + \varphi_{d,2}\widetilde{v}_{f,t-1}$$

New-York regression : $r_{f,t} = \mu_f + \psi_{f,t}\xi_{f,t} + \widetilde{\varphi}_{f,t} r_{d,t} + \epsilon_{f,t}$

$$\psi_{f,t} = \psi_{f,1} + \psi_{f,2}\left|\xi_{f,t}\right| + \psi_{f,3}\widetilde{v}_{d,t} + \psi_{f,4}\widetilde{v}_{f,t-1}$$

$$\widetilde{\varphi}_{f,t} = \varphi_{f,1} + \varphi_{f,2}\widetilde{v}_{d,t}$$

$\widetilde{v}_{d,t}(\widetilde{v}_{f,t})$ - standardized trading volume on Tokyo (New-York) market

$r_{d,t}(r_{f,t})$-close-to-close return on Tokyo (New-York) market

$^{*(**)}$ indicates significance at 10 (5) %

Table 7 *(continued)*: **Volume-return dynamics (close-to-close returns)**

	Nissan	Honda	Sony	TDK	Toyota
Ordinary Share - TSE					
φ_2	-0.048^{**} (0.021)	-0.004 (0.022)	-0.008 (0.023)	-0.055^{*} (0.032)	-0.006 (0.023)
ψ_3	0.129^{**} (0.05)	0.096^{**} (0.039)	0.051^{*} (0.028)	0.16^{**} (0.055)	0.001 (0.04)
ψ_4	0.024 (0.041)	-0.094^{**} (0.041)	-0.06^{**} (0.02)	0.094 (0.058)	0.135^{**} (0.04)
$H_0 : \varphi_2 = \psi_3 = 0$	0.026	0.046	0.004	0.011	0.96
ADR - NYSE (NASDAQ)					
φ_2	0.006 (0.014)	-0.014 (0.013)	-0.056^{**} (0.01)	-0.017 (0.015)	-0.028^{**} (0.01)
ψ_3	-0.006 (0.017)	0.01 (0.019)	0.056^{**} (0.022)	0.0063 (0.02)	0.012 (0.017)
ψ_4	0.008 (0.012)	0.001 (0.013)	0.055^{**} (0.022)	0.016 (0.009)	0.032^{**} (0.013)
$H_0 : \varphi_2 = \psi_3 = 0$	0.91	0.29	0.0000	0.09	0.02

Tokyo regression : $r_{d,t} = \mu_d + \psi_{d,t}\xi_{d,t-1} + \widetilde{\varphi}_{d,t} r_{f,t-i} + \epsilon_{d,t}$

$$\psi_{d,t} = \psi_{d,1} + \psi_{d,2}\left|\xi_{d,t-1}\right| + \psi_{d,3}\widetilde{v}_{f,t-1} + \psi_{d,4}\widetilde{v}_{d,t-1}$$

$$\widetilde{\varphi}_{d,t} = \varphi_{d,1} + \varphi_{d,2}\widetilde{v}_{f,t-1}$$

New-York regression : $r_{f,t} = \mu_f + \psi_{f,t}\xi_{f,t} + \widetilde{\varphi}_{f,t} r_{d,t} + \epsilon_{f,t}$

$$\psi_{f,t} = \psi_{f,1} + \psi_{f,2}\left|\xi_{f,t}\right| + \psi_{f,3}\widetilde{v}_{d,t} + \psi_{f,4}\widetilde{v}_{f,t-1}$$

$$\widetilde{\varphi}_{f,t} = \varphi_{f,1} + \varphi_{f,2}\widetilde{v}_{d,t}$$

$\widetilde{v}_{d,t}(\widetilde{v}_{f,t})$ - standardized trading volume on Tokyo (New-York) market

$r_{d,t}(r_{f,t})$-close-to-close return on Tokyo (New-York) market

$^{*(**)}$ indicates significance at 10 (5) %

3.A The List of Sample Companies

Firm Name	Industry Code	Japan Listing	US Listing	US listing date
Canon	3577	TSE	NYSE	14/09/2000
Fuji Photo Film Co. Ltd	3861	TSE	NASDAQ	10/03/1993
Hitachi Limited	3570	TSE	NYSE	14/04/1982
Kyocera Corporation	3663	TSE	NYSE	23/05/1980
Matsushita Electric Industrial Co	3600	TSE	NYSE	13/12/1971
Nissan Motor Co Ltd.	3711	TSE	NASDAQ	16/03/1994
Honda Motor Co Ltd	3711	TSE	NYSE	11/02/1977
Sony Corporation	3651	TSE	NYSE	17/09/1970
TDK Corporation	3679	TSE	NYSE	15/06/1982
Toyota Motor Corporation	3711	TSE	NYSE	29/09/1999

3.B Specifications tests

3.B.1 Error-Correction Dynamics

In this part of the Appendix we conduct specification tests of the dynamics of the error correction mechanism of the cross-listed securities. Under the null hypothesis the error correction occurs in a linear fashion, that is, $m(x_j) = E(r|x_j) = \alpha + \beta \cdot x_j$. We formally test the hypothesis of non-linear vs linear adjustment based on the following test statistic, proposed by Gozalo (1993)

$$\hat{T}_j = (nh)^{1/2} v_1^{-1/2} \left(\hat{m}^{np}(x_j) - \hat{m}^{p}(x_j) \right)$$

where $\hat{m}^{np}$ is a nonparametric kernel estimate of the conditional mean, $\hat{m}^{p}$ is its parametric estimate under the null estimated by least squares and $v_1 = f(x_j)^{-1}\sigma^2 \int K(\psi)^2 d\psi$ with $f(\cdot)$ being a density function of x evaluated at the point x_j and $K(\cdot)$ being a kernel. Under the null of correct parametric specification the limit distribution of the test statistic is standard normal. Following Gozalo, we look at the supremum of $\hat{T}$ evaluated at d randomly chosen points. Since this test is potentially oversized we also calculate the statistic $G = \sum_{j=1}^{d} \hat{T}_j^2$

which has $\chi^2(d)$ distribution under the null. Since the results of the non-parametric test can be sensitive to the choice of the bandwidth we also estimate polynomial approximation of $m^{np}$by least squares and test the null that the coefficients of the high-order terms are jointly equal to zero via a standard Wald test. The number of high-order terms is chosen by minimizing Akaike Information Criterion. For each firm the null of a linear adjustment mechanism is tested separately for the ordinary share and its ADR.

Table B.1:Tests of the linearity of the error-correction dynamics

	ADR			Ordinary share		
	Sup(T)	G	Wald	Sup(T)	G	Wald
Canon	0.011	0.022	0.00	0.03	0.27	0.008
Fuji	0.03	0.035	0.00	0.22	0.91	0.035
Hitachi	0.024	0.06	0.02	0.14	0.06	0.31
Kyocera	0.006	0.045	0.002	0.09	0.34	0.003
Matsushita	0.012	0.02	0.00	0.5	0.98	0.45
Nissan	0.03	0.021	0.004	0.26	0.56	0.4
Honda	0.06	0.21	0.00	0.01	0.02	0.00
Sony	0.01	0.023	0.00	0.03	0.34	0.75
TDK	0.05	0.65	0.05	0.16	0.89	0.5
Toyota	0.013	0.023	0.002	0.03	0.08	0.18

The numbers reported are the p-values of the Gozalo and Wald specification tests as described in Appendix 3.B.1. Throughout this paper we use a Gaussian kernel. The results are fairly robust to different choices of the bandwidth

3.B.2 Skewness Dynamics

Let us define by $z_{d,t}$ and $z_{f,t}$ the standardized errors for the ordinary share and its underlying ADR, respectively, which can be consistently estimated within a Quasi-Maximum Likelihood framework. Since by the definition the skewness $s_t = E_{t-1}(z_t^3)$ as a preliminary analysis it seems reasonable to study the dynamics of z's and, in particular, to test for the non-linear dependence and for the possibility of autoregressive dynamics. We test the former via BDS while the latter is tested via the autocorrelation function (ACF) of the cubic standardized innovations. The results are presented in Table B.2.

For most of the companies, we find no evidence of an autoregressive non-linear dependence for the normalized innovations. The analysis of the autocorrelation function also suggests that, in general, there is no evidence of skewness being persistent. Overall, our preliminary analysis fails to detect any autoregressive dynamics in the conditional distribution of the standardized innovations

Table B.2: Skewness dynamics-preliminary analysis

	BDS_{z_d}		BDS_{z_f}		$ACF_{z_d^3}$			$ACF_{z_f^3}$		
	2	4	2	4	ρ_{-1}	ρ_{-5}	ρ_{-10}	ρ_{-1}	ρ_{-5}	ρ_{-10}
Canon	0.61	0.53	0.79	0.29	0.03	0.001	0.004	0.005	-0.007	0.001
Fuji	0.67	0.49	0.09	0.04	0.02	0.01	0.04	-0.04	0.007	0.002
Hitachi	0.92	0.28	0.97	0.11	-0.02	-0.03	0.007	0.02	-0.002	0.006
Kyocera	0.79	0.26	0.05	0.05	0.02	0.02	-0.02	0.01	-0.08**	0.003
Matsushita	0.34	0.21	0.49	0.34	-0.03	-0.01	0.057	0.03	-0.06**	0.058
Nissan	0.65	0.21	0.93	0.96	0.03	0.03	0.057	0.01	-0.02	0.02
Honda	0.29	0.41	0.98	0.46	0.02	0.072**	0.031	0.007	0.02	0.02
Sony	0.3	0.07	0.8	0.72	0.01	0.004	0.003	0.15**	0.001	-0.01
TDK	0.98	0.75	0.63	0.88	0.006	-0.02	-0.02	0.03	-0.024	0.048
Toyota	0.86	0.64	0.23	0.16	-0.007	0.01	-0.005	0.008	-0.03	0.018

BDS_{z_d} and BDS_{z_f} are the p-values of the BDS test applied to the standardized returns on the Tokyo/US markets
ρ_{-1}, ρ_{-5} and ρ_{-10} are the sample serial correlations of the cubic standardized returns on the Tokyo/US markets

3.C Hansen's Skewed Student-t Density- A Brief Review

Hansen's skewed Student-t distribution can be described by the following density function

$$g(z\,|\lambda,\eta) = \begin{cases} bc\left(1+\frac{1}{\eta-2}(\frac{bz+a}{1-\lambda})^2\right)^{-(\eta+1)/2} & \text{for} \quad z < -\frac{a}{b} \\ bc\left(1+\frac{1}{\eta-2}(\frac{bz+a}{1+\lambda})^2\right)^{-(\eta+1)/2} & \text{for} \quad z \geq -\frac{a}{b} \end{cases}$$

where $2 < \eta < \infty$, and $-1 < \lambda < 1$. The constants a, b, and c are given by

$$a = 4\lambda c \left(\frac{\eta - 2}{\eta - 1} \right)$$

$$b^2 = 1 + 3\lambda^2 - a^2$$

$$c = \frac{\Gamma\left(\frac{\eta+1}{2}\right)}{\sqrt{\pi(\eta - 2)}\Gamma\left(\frac{\eta}{2}\right)}$$

It can be shown that this is a proper density function with a mean of zero and a unit variance (see Hansen (1994), Appendix 1). Furthemore, Jondeau and Rockinger (2003) show that the formulae for skewness and kurtosis are given by

$$E(z^3) = (m_3 - 3am_2 + 2a^3)/b^3$$

$$E(z^4) = (m_4 - 4am_3 + 6a^2m_2 - 3a^4)/b^4$$

where the constants m_2, m_3 and m_4 are given by

$$m_2 = 1 + 3\lambda^2$$

$$m_3 = 16c\lambda(1 + \lambda^2)\frac{(\eta - 2)^2}{(\eta - 1)(\eta - 3)} \quad \text{for } \eta > 3$$

$$m_4 = 3\frac{\eta - 2}{\eta - 4}(1 + 10\lambda^2 + 5\lambda^4) \quad \text{for } \eta > 4$$

Chapter 4

Trading Volume, Volatility and Return Dynamics: Individual and Cross-Market Analysis

4.1 Introduction

The purpose of this paper is to study the dynamic relationship between stock returns, trading volume, and volatility. Both trading volume and volatility attract a lot of attention of both academics and practitioners. This indicates their potential importance as indicators of the current stock market activity on the one hand, and a potential source of information regarding the underlying fundamentals, and, thus, the future behavior of stock markets, on the other hand. Obviously, if stock markets are informationally efficient, that is, if all information is fully incorporated in the stock prices, studying the links between future stock returns, volume, and volatility would be pointless. However, numerous pricing anomalies reported in the finance literature suggest that the price discovery process is not immediate. But then both trading volume and volatility might serve as useful indicators regarding the extent to which pricing information is impounded in security prices and, thus, they may have some predictive power regarding the future behavior of stock prices.

This research is motivated by a rapidly growing field of academic literature which focuses on the predictability of stock returns and, in particular, the role of the trading volume and the volatility in the dynamics of the price discovery process. A surge in academic literature, both theoretical and empirical, on the volume (volatility)-return relation reflects the need of further understanding of the underlying processes generating trading on the other hand and security price changes on the hand. In particular, since volume and volatility both serve as measures of information flow (see, for instance, Andersen, 1996), examining the links between stock returns, volume, and volatility provides a further understanding of how new information is impounded in stock prices. However, the interest in this field is not limited to the academic community only. Nowadays, stock markets are becoming increasingly more complex in their structure but also more competitive on the other. The increased accessibility of information and investors searching for arbitrage opportunities caused many previously recorded pricing "anomalies" to disappear or to lose their economic significance (Schwert, 2003). In this context, a deeper understanding of the role of the trading volume and the volatility in the dynamics of security prices may help investors to identify future patterns of the stock market which can be exploited in their investment decisions.

This paper has three contributions to the literature. First, the majority of studies examining the role of the trading volume and volatility in the dynamics of the stock returns do this in a parametric setting, usually postulating some parametric specification for the return generating process. This approach may lead to erroneous conclusions due to potential model misspecification. Instead, in our study we rely on a nonparametric approach, an approach which is not only easy to implement, but also does not require any specific assumptions regarding the data generating process. Second, while most of the previous studies concentrate on examining only one specific relationship (volume-volatility, volatility-autocorrelation, and so on), we study the dynamics of the stock returns by controlling for *both* trading volume *and* volatility effects. This approach, as we show, sheds a new light on some stylized facts described in the empirical volume-return literature. Finally, we extend our analysis to a multiple market setting, where we study the role of the trading volume and volatility in a cross-border information transfer, based on a large sample of cross-listed firms. Using cross-listed securities (instead of market indices) allows us to study the mechanism of the cross-border information transfer, while controlling for the individual firm characteristics.

Our major findings are as follows. First, we find no evidence of the trading volume having any direct impact on the serial correlation of stock market returns. Second, we find that the serial correlation of stock market returns is inversely related to the stock market volatility. Moreover, we find that while the high frequency returns are reported to be unconditionally positively serially correlated, taking into account volatility effects, the serial correlation coefficients turn out to be negative during periods of high market turbulence. Third, we find that an increase in the volume leads to a subsequent increase in the stock market volatility. Together, these three findings shed a new light on the volume-return reversal relationship documented by many studies. In contrast to these studies our findings suggest that it is the stock market volatility that plays a major role in the magnitude and the sign of the return reversal, while trading volume plays a secondary role. Finally, we find that the trading volume plays an important role in a multiple market setting, and, in particular, in the price discovery process and in the co-movement between stock markets, supporting the informative role of the trading volume for investors.

This remainder of the paper is organized as follows. In Section 4.2 we review the existing literature on the volume-volatility-return dynamics. Section 4.3 describes the data. In Section 4.4 we discuss the methodology used in our study. In Section 4.5 we define our hypotheses. Estimation results are presented and discussed in Section 4.6. Finally, in Section 4.7 we make our concluding remarks and discuss some potential directions for further research.

4.2 Literature Review

In this section we review the existing literature on the relationship between trading volume, volatility, and stock returns. We start in subsection 4.2.1 with a brief review of the academic work which focuses on the impact of the trading volume on the serial correlation of stock returns. Next, in subsection 4.2.2 we summarize the literature on the volatility-serial correlation dynamics. Subsection 4.2.3 provides a brief summary of the studies examining the trading volume-expected returns and trading volume-volatility relationships. Finally, in subsection 4.2.4 we review the literature on the volume-return dynamics in a multiple market setup.

4.2.1

4.2.2 Trading Volume and Serial Correlation Relations

A number of theoretical models linking the lagged trading volume and serial correlation of stock returns have been proposed. Campbell, Grossman and Wang (1993) introduce a model where such a link is related to non-informational trading. In their model there are two types of investors both with Constant Absolute Risk Aversion (CARA) utility function. The first type has a constant risk aversion parameter, while the risk aversion of the second type may change over time. Trading is induced by, and is positively related to the changes (in absolute value) in the risk aversion of the type 2 investors, which leads to an increase in the expected return rewarding the type 1 investors for accommodating the buying/selling pressure. The implications of this model are that the serial correlation of the stock returns is negatively related to the trading volume. Wang (1994) generalizes the model of Campbell *et al.* (1993) by allowing for information asymmetry among the investors. In his model informational and non-informational trading lead to a different dynamic relationship between the trading volume and the serial correlation of the stock returns. Llorente, Michaely, Saar, and Wang (2002) present a simplified version of the Wang (1994) model in which investors trade either to share risk or to speculate on private information. In their model returns generated by risk-sharing trades exhibit a negative autocorrelation while the returns generated by the speculative trades are positively serially correlated.

The relationship between the lagged trading volume and the serial correlation of stock returns has been a focus of a substantial body of empirical studies as well. Dufee (1992) studies the relation between the serial correlation and trading volume using aggregate monthly US data. He reports a statistically significant relationship between volume shocks and return reversals. Campbell *et al.* (1993) report a negative relationship between the lagged trading volume and the serial correlation of stock market returns for the US data at a daily frequency. Conrad, Hameed, and Niden (1994) examine the profitability of weekly contrarian strategies based on a high/low volume filtration for stocks listed on the US stock markets. They report that a high number of transactions is associated with a return reversal in subsequent periods, while a low volume is more likely to generate momentum. Bremer and Hiraki (1999) explore the serial correlation-volume dynamics of the stocks listed on the Tokyo Stock Exchange. They report that loser stocks with a high trading volume tend to have larger price reversals in the following week. On the contrary, Cooper (1999) reports that for large capitalization stocks a decline in volume is associated with return reversals and vice versa. A positive relationship between the magnitude of momentum and the lagged turnover is also reported by Lee and Swaminnathan (2000), and Chan *et al.* (2000). Overall, these findings suggest that the likelihood of observing a reversal or "momentum" in stock returns is related to trading volume.

4.2.3 Stock Return Volatility and Serial Autocorrelation Relations

The link between volatility and serial correlation in stock returns has been suggested by Sentana and Wadhwani (1992) in their so-called "feedback trading" model. In this model two types of investors are assumed to be present: mean-variance (or "smart money") traders and feedback traders, whose demand is assumed to be a function of past stock returns. This function is increasing in past returns if the investors follow a "positive feedback" investment strategy ("momentum") and decreasing if they follow a "negative feedback" ("contrarian") strategy. Sentana and Wadhwani (1992) show that in equilibrium the serial correlation of the stock returns is decreasing (increasing) in the stock return volatility if the investors are "momentum" ("contrarian") traders.

A number of empirical studies has been conducted in this field. LeBaron (1992) explores the relation between serial correlation and volatility for several different stock return series at both daily and weekly frequencies for the US markets. He reports a negative relation between the serial correlation of the stock returns and the volatility, a finding which is consistent with investors following a "positive feedback" strategy. Sentana and Wadhwani (1992) report similar results based on a large span of daily data on a US aggregate stock market index. Koutmous (1996) extends these previous studies beyond the US market borders by studying the impact of volatility on the serial correlation for several other national markets. His findings are similar to those reported by LeBaron (1992) and Sentana and Wadhwani (1992), suggesting that the volatility-serial correlation relationship is not likely to be induced by the microstructure specifics of a particular market.

4.2.4 Expected Return-Volume and Volatility-Volume Relations

A number of studies examine the relationship between the lagged trading volume and expected returns. Gervais *et al.* (2001) suggest that the existence of such a link can be attributed to the so-called "visibility" hypothesis. They argue that an unusually high volume makes the stock more "visible" to investors and, thus, attracts new traders. In the presence of short-selling constraints an additional buying pressure will dominate, thus, leading to higher returns in the following periods. On the other hand, Baker and Stein (2003) propose an alternative view by interpreting liquidity indicators (and among them trading volume/share turnover) as a measure of investors' sentiment. In their model they assume the existence of irrational investors who underreact to the information contained in the order flow, thus, boosting liquidity. In the presence of short-selling constraints this class of investors is active in the market only when their sentiment is positive. Therefore, a high trading volume is an indicator that the market is overvalued, leading to subsequent lower returns. Brennan and Subrahmanyam (1996), and Brennan, Chordia, and Subrahmanyam (1998) find that a high share turnover is associated with lower future returns in a cross section of individual firms. On the other hand, Gervais *et al.* (2001) report that investment strategies based on buying the stocks which experienced an unusually high volume and selling those with previously a low volume, yield positive and statistically significant returns. For the aggregate stock markets, Jones (2001) finds that a high turnover leads to subsequent lower returns of the Dow-Jones index.

In contrast to the trading volume-expected return theories, the link between trading volume and volatility is mostly related to a "mixture of distribution" or "information flow" hypothesis, introduced by Clark (1973). This hypothesis posits a joint dependence of returns and volume on an underlying information flow variable. Since there is a wide consensus that the trading volume is highly positively autocorrelated, one of the implications of this theory is that the stock return volatility should also be positively related to the lagged trading volume. Lamourex and Lastrapes (1990) find strong evidence of the trading volume positively affecting the variance for a sample of common stocks traded on the US market. Andersen (1996) develops an empirical return volatility-volume model based on a microstructure framework. Lee and Rui (2002) report a positive feedback relationship between the trading volume and volatility on the US, UK, and Japanese stock markets. Similar results are reported by Gerlach *et al.*(2006) for selected samples of Asian and European stock markets.

The documented volatility-volume and volatility-autocorrelation relations are particularly important in the context of this study. Together, these findings present an alternative explanations for the reported volume-autocorrelation relation. It is possible that trading volume affects the serial correlation of stock returns not directly, but *indirectly* via volatility, This hypothesis, among others, will be tested in the following sections.

4.2.5 Volume, Volatility, and Return Dynamics in a Multiple Asset Framework.

While there exists an extant body of academic literature studying the relations between trading volume, volatility, and the dynamics of stock returns in a single asset (or market) framework, the literature discussing these dynamics in a multiple asset/market framework is quite sparse. Taking into account that stock markets are becoming increasingly sophisticated and more globally integrated this gap is indeed surprising. Studying the role of the trading volume and volatility in the dynamics of stock returns in a multiple asset framework may provide important clues on optimal portfolio selection, while examining the volume-volatility-return dynamics in a multiple market framework may contribute to our understanding of the cross-border information flow mechanism between the markets.

Chordia and Swaminathan (2000) study the possibility of using the trading volume to forecast short horizon returns on stocks traded on the US stock markets. They find that daily returns of stocks with low trading volume are led by those with high trading volume. They attribute this finding to actively traded stocks having a higher speed of adjustment to new information. Lee and Rui (2002) report the US trading volume having a significant causal effect on the returns and volatility of the UK and Japanese stock markets. Gagnon and Karolyi (2003) study the impact of the trading volume on the spill-overs between and the comovement of the Japanese and US stock market indices. They find that following days with a high volume the cross-market correlation coefficients become significantly smaller. They attribute this finding to the trading volume serving as a proxy for liquidity shocks, as in the Campbell *et al.* (1993) model. These findings provide some preliminary evidence of the role of the trading volume in a multiple asset/market setting, a role which will be further studied in this paper.

However, in contrast to Lee and Rui (2002) and Gagnon and Karolyi (2003) who examine the role of the trading volume in the dynamics of the aggregate stock market indices, we focus on the cross-listed securities. By studying the same security listed on multiple markets it allows one to control for various firm-specific characteristics, which could potentially affect the role of trading volume in the dynamics of stock returns.

4.3 Data Description and Preliminary Data Analysis

Our dataset consists of daily data on the closing trading level and volume of nine major developed stock markets: the US, United Kingdom, Germany, Japan, Italy, the Netherlands, Canada, France, and Australia. We also include the Hong-Kong stock market which is considered to be the largest and one of the most influential among the emerging stock markets. All data has been obtained from Datastream International. In Table 1 we list our specific indices, the sample period, and the number of observations for each market after excluding holidays, and the trading days with missing observations.

As for the cross-listed securities, our dataset also includes all Canadian firms which were listed on both the Toronto Stock Exchange (TSE) and the NYSE/AMEX during the period January 2000-December 2005 as ordinary shares (CRSP code 12). To be included in our sample a company must have at least one year of data after excluding two months since its listing or before its delisting, in order to take care of potential post-listing or pre-delisting effects. After deleting a number of companies with missing observations from our sample this screening rule leaves us with a total number of 107 firms.

The descriptive statistics of the daily close-to-close log returns on the national stock market indices are reported in Table 1. All markets exhibit a positive (though statistically insignificant) drift over time. The stock market returns also appear to be slightly negatively skewed, implying that there is a higher probability of observing negative returns. For Canada, the Netherlands, Germany, and Australia the skewness sample estimates are also statistically significant. On the other hand, for all markets the sample estimates of the kurtosis are significantly higher than the one implied by the normal distribution, a finding which is supported by the high values of the Jarque-Bera statistic. Most of the unconditional non-normality seems to be due to leptokurtosis. Some of the stock markets' daily returns also exhibit positive and statistically significant first-order autocorrelation which, however, seems to dissipate rapidly at the higher-order lags, suggesting that the potential reason for this serial autocorrelation is the non-synchronous trading of the index components.

Table 1: Descriptive statistics of daily market returns

Country	US	UK	Canada	Japan	Italy
Market Index	S&P 500	FTSE 100	TSX	TOPIX	DS Index
Sample Period	01/91-12/2005	06/88-12/2005	01/91-12/2005	01/91-12/2005	01/91-12/2005
No obs.	3782	4451	3777	3708	3790
Mean	0.0004	0.0003	0.0003	0.0002	0.0003
St.Dev	0.01	0.011	0.009	0.012	0.013
Skewness	-0.09	-0.12	-0.71*	0.06	-0.16
Kurtosis	6.88**	6.15**	10.44**	5.95**	5.81**
$\rho_{t,t-1}$	-0.002	0.019	0.11**	0.086**	0.059**
J-B stat.	2376.1**	1855.9**	9054.63**	1349.9**	1264.7**
Country	Netherlands	Hong-Kong	Germany	France	Australia
Market Index	DS Index	Hang-Seng	DS Index	CAC 40	AORD
Sample Period	02/86-12/2005	01/91-12/2003	06/88-12/2005	01/92-12/2005	03/00-12/2005
No obs	4995	3504	4431	3311	1444
Mean	0.0002	0.0004	0.0003	0.0002	0.0003
St.Dev	0.01	0.017	0.011	0.014	0.007
Skewness	-0.49**	-0.015	-0.66**	-0.089	-0.93**
Kurtosis	10.16**	12.3**	10.12**	5.46**	10.55**
$\rho_{t,t-1}$	0.01	0.034*	0.053**	0.016	-0.015
J-B stat.	9681.6**	12609.9**	9702.4**	836.6**	3639.4**

$\rho_{t,t-1}$ is the estimate of the first-order serial correlation between the stock index returns

J-B stat. is the value of a Jarque-Berra statistic applied to a stock index returns

*(**) denotes significance at 10 (5) %. For kurtosis denotes that the latter is significantly different from 3

Next, we turn to a preliminary analysis of the trading volume series. In this research we define "trading volume" as the total number of shares traded at a particular day. Both earlier (Gallant and Tauchen (1992)) and more recent studies (including, for example, Lee and Rui (2002)) report non-linear trends in the trading volume series. Since we wish to work with stationary data, we follow Lee and Rui (2002) by replacing the raw trading volume v_t by a de-trended one $\left(\widetilde{v}_t\right)$ which is obtained as the estimated residual from the regression

$$v_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \widetilde{v}_t.$$

In Table 2 we present the sample estimates of the regression β-s. For all markets we find highly significant non-linear time trends, with the slope coefficients being highly statistically significant. Also, based on standard unit root tests, such as the Augmented Dickey-Fuller and Phillips-Perron tests, we conclude that the trading volume series are trend stationary. While the higher-order coefficients appear to be significant as well, an examination of the de-trended volume plots suggests that including a linear and quadratic time trend removes any visible time trend from the trading volume series. Thus, following Lee and Rui (2002) for the national stock market indices we shall adopt these de-trended volumes as the basic measure of trading activity in the subsequent analysis. To assess the robustness of our findings, we shall also consider alternative methods of removing low-frequency variations which will be discussed in the following sections.

Table 2: Time trend in trading volume					
Country	USA	UK	Canada	Japan	Italy
β_0	-41.9^{**} (14.06)	221.9^{**} (12.1)	742.9^{**} (107.8)	501.3^{**} (13.8)	-82.8^{**} (7.5)
β_1	228.9^{**} (17.17)	-214.2^{**} (11.43)	283.4^{**} (13.2)	-445.7^{**} (17.2)	288.8^{**} (9.1)
β_2	0.1^{**} (0.004)	0.12^{**} (0.002)	0.02^{**} (0.003)	0.22^{**} (0.004)	-0.02^{**} (0.002)
ADF stat.	-6.06**	-6.63**	-12.11**	-10.42**	-7.07**
Country	Netherlands	Hong-Kong	Germany	France	Australia
β_0	-4.2^{**} (1.23)	2101^{**} (188.9)	-37.1^{**} (2.5)	6.4^{**} (1.4)	261.2^{**} (12.6)
β_1	2.82^{**} (1.14)	-2959^{**} (235.6)	84.3^{**} (2.6)	-12.8^{**} (3.4)	399.7^{**} (45.8)
β_2	0.06^{**} (0.0002)	2.11^{**} (0.06)	-0.02^{**} (0.0006)	0.02^{**} (0.001)	-0.11^{**} (0.03)
ADF stat.	-4.35**	-5.89**	-4.91**	-4.55**	-10.9**

Estimated regression: $v_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \widetilde{v}$

ADF stat. denotes statistic of the Augmented Dickey-Fuller test applied to the estimated residuals $\widetilde{v}$.*(**) denotes significance at 10 (5) %

Next, we present descriptive statistics for the sample of firms, whose shares are cross-listed on both the Toronto Stock Exchange (TSE) and the US stock markets (NYSE/AMEX). For each statistic (mean, standard deviation, *etc*) we present a cross-sectional average of its sample estimate for all the firms included in our sample. We start with an analysis of the descriptive statistics of the daily close-to-close log returns, which are presented in the upper panel of Table 3. Both the New York and Toronto listed shares exhibit a positive and statistically significant drift. Also, during our sample period both the New York and Toronto shares are characterized by a relatively high volatility, about 47 percent in annual terms. This could be due to the fact that our sample includes the period of the "dot.com" bubble collapse and also the period of high turbulence during the second half of 2002, which followed the series of severe bankruptcy scandals. Interestingly, the average estimates of the volatility of the US and Canada-listed shares are very close. Since the volatility is often considered to be a proxy for the information flow (see, for instance, Andersen (1996), among others), this preliminary finding suggests that the intensity of the information flow on the domestic and foreign market is of a similar magnitude.

This may be due to the fact that both stock exchanges have perfectly overlapping trading hours. As a result, the information revealed during a business day on one market is rapidly reflected in the stock prices on the other market. Stock returns on both market also appear to be slightly positively skewed, though the average estimates of the skewness lack statistical significance. The returns on both market are leptokurtic with the average estimates of the excess kurtosis being highly statistically significant. For both markets we find no evidence of returns being serially correlated. However, the returns appear to be cross-autocorrelated with the average estimates of the cross-autocorrelation coefficients being positive and statistically significant. Also, the squared returns exhibit a substantial degree of serial and cross-autocorrelation, suggesting the presence of ARCH and volatility spillover effects.

Descriptive statistics of the daily trading volume are presented in the lower panel of Table 3. On average, the trading volume appears to be higher on Toronto Stock Exchange, suggesting that the trade is concentrated on the domestic market. A comparison of the estimates of the standard deviations suggests that trading on the TSE is also more volatile. Both market volumes are significantly positively skewed and also leptokurtic. Interestingly, the average estimate of the kurtosis is substantially higher for the TSE, a finding which again suggests that trading on the domestic market appears to be more turbulent. Finally, consistent with other studies, the market trading volumes exhibit both an economically and statistically significant positive serial correlation. Also, the estimates of the cross-market serial correlation, $\text{Corr}(v_{US,t}, v_{CAN,t-1})$ and $\text{Corr}(v_{CAN,t}, v_{US,t-1})$, suggest the existence of cross-market volume spill-overs.

Table 3: Cross-listed firms-descriptive statistics							
Table 3.A: Descriptive statistics of daily returns							
Mean		St.Dev		Skew.		Kurt	
New-York	Toronto	New-York	Toronto	New-York	Toronto	New-York	Toronto
0.0004**	0.0004**	0.03	0.029	0.1	0.016	13.21**	10.18**
$Corr(r_{US,t}, r_{US,t-1})$		$Corr(r_{CAN,t}, r_{CAN,t-1})$		$Corr(r_{US,t}, r_{CAN,t-1})$		$Corr(r_{CAN,t}, r_{US,t-1})$	
-0.001		0.001		0.063**		0.051**	
$Corr(r^2_{US,t}, r^2_{US,t-1})$		$Corr(r^2_{CAN,t}, r^2_{CAN,t-1})$		$Corr(r^2_{US,t}, r^2_{CAN,t-1})$		$Corr(r^2_{CAN,t}, r^2_{US,t-1})$	
0.126**		0.121**		0.114**		0.11**	
Table 3.B: Descriptive statistics of trading volume (thousands of shares)							
Mean		St.Dev		Skew		Kurt	
New-York	Toronto	New-York	Toronto	New-York	Toronto	New-York	Toronto
619.2**	875.6**	614.3	836.7	5.18**	5.99**	60.79**	77.8**
$Corr(v_{US,t}, v_{US,t-1})$		$Corr(v_{CAN,t}, v_{CAN,t-1})$		$Corr(v_{US,t}, v_{CAN,t-1})$		$Corr(v_{CAN,t}, v_{US,t-1})$	
0.508**		0.34**		0.251**		0.25**	

$r_{US}(r_{CAN})$ denotes log-return of the cross-listed shares on the New-York (Toronto) stock exchange. $v_{US}(v_{CAN})$ denotes trading volume of the cross-listed share on the US (Toronto) stock exchange. ** denotes significance at 5%, for kurtosis denotes significant difference from 3

4.4 Methodology

The major interest of this research is to study potential interactions between trading volume, volatility, and the dynamics of stock returns. We start the analysis with a model which requires a minimal set of assumptions, and, thus, reduces the possibility of reaching the wrong conclusions due to misspecification of the functional form. Let y be the dependent variable, x be the explanatory (conditioning) variable and let $E(\cdot)$ denote the expectation operator. The following decomposition of y can be considered

$$y = m(x) + \epsilon, \quad E(\epsilon\,|x) = 0$$

with $m(x)$ being (by definition) the conditional expectation of y given x. For instance, y can be the return of a specific stock market index and x can be the corresponding lagged trading volume. Then, by testing the null hypothesis that $\frac{\partial m(x)}{\partial x} = 0$ we test for the presence of a causal effect between trading volume and stock market returns. Clearly, a correct specification of $m(\cdot)$ plays a crucial role. Therefore, we start our analysis within the semi-nonparametric framework. More specifically, we use a Flexible Fourier Form (FFF) series approximation as proposed by Gallant (1982). Within this framework the estimate of the conditional moment $m(x)$ is given by

$$\hat{m}(x) = a_n + b_n x + c_n x^2 + \sum_{\ell=1}^{\frac{M_n}{2}} (\varphi_{\ell,n} \cos(\ell x) + \phi_{\ell,n} \sin(\ell x)),$$

where x is the conditioning variable which in our case is the lagged trading volume $\widetilde{v}$ or the conditional volatility h, M_n is the total number of trigonometric expansion terms to be chosen, and $[a, b, c, \varphi, \phi]$ is the vector of parameters which can be estimated either via least squares or using a Quasi-Maximum Likelihood framework. This method can easily be extended to more complex moment based estimators: for instance, the conditional variance of the stock market returns can be estimated via a two-step procedure. First, the conditional expectation of the stock market returns is estimated within the FFF framework. Next, the squared deviations from the conditional mean are calculated and used as the dependent variable to estimate the conditional variance. A similar approach can be used to estimate more complex moments, such as the first-order conditional autocovariance, *etc.* For instance, one can consistently estimate the dynamics of the conditional first-order autocorrelation coefficient by estimating the conditional variance and the first order autocovariance of the stock returns, which might provide a valuable insight into the role of the trading volume and the volatility in the dynamics of stock return reversals/momentum over time. However, a number of issues should be kept in mind while applying a FFF series approximation. First, as pointed out by Gallant (1982), the conditioning variable x should be restricted to lie between $(0, 2\pi)$ (see also Pagan and Ullah,1994). When the conditioning variable is the detrended volume $\widetilde{v}$, we replace it by $x = 2\pi \frac{\exp(\widetilde{v})}{1+\exp(\widetilde{v})}$, that is, we apply a simple logistic transformation to the detrended volume. When the conditioning variable is the volatility h we replace it by $x = 2\pi \frac{h \cdot 10^3}{1+h \cdot 10^3}$. A second issue concerns the choice of the truncation window. Unfortunately, there is no clear-cut rule of how to choose the number of expansion terms. Andrews (1991) finds that M_n can be of the order of magnitude between

$O(n^{1/3})$ and $O(n^{1/5})$. Obviously, this is not too helpful, even if we would know what the "optimal" order of expansion should be, since it still leaves us with an unknown constant factor. Hence, we choose M $_n$ to be equal to $n^{1/4}$, which leads to a value of M equal to eight for most of the indices in our study. In the following sections we shall also test the robustness of our findings to alternative choices of the truncation window.

Estimating the conditional moments of the stock returns within the FFF framework provides a straightforward and easy to implement way to study the predictive power of the trading volume and the stock return volatility. Indeed, all issues investigated in this study can be reformulated in terms of restrictions on the dynamics of the conditional moments, and in this context the FFF methodology seems to be a natural way to proceed, since it provides consistent estimators (under appropriate regularity conditions, including $M_n \to \infty$), while, from the perspective of calculating the estimator, it is a standard parametric approach. But, as is typical for any non-parametric estimator, it suffers from the"curse of dimensionality" requiring quite a lot of observations for accurate estimation when more regressors are considered at the same time. Therefore, we shall also study the predictive power of the trading volume and volatility within the parametric framework, as will be discussed in the following sections.

4.5 Hypotheses Development

4.5.1 Individual Stock Markets

We start with the hypotheses development for the single-market setup. Define by r the daily close-to-close log-return of a specific stock market index. Also, let v and h stand for the trading volume and the volatility of that particular stock market index, respectively. For the trading volume the following null hypotheses are considered

$$\textbf{H1}: \quad \frac{\partial E(r_{t+1}\,|v_t)}{\partial v_t} = 0$$

$$\textbf{H2}: \quad \frac{\partial Var(r_{t+1}\,|v_t)}{\partial v_t} = 0$$

$$\textbf{H3:} \quad \frac{\partial Cov(r_{t+1}, r_t\,|v_t)}{\partial v_t} = 0$$

The first hypothesis postulates no causal effects between the stock market returns and the corresponding lagged trading volume. More specifically, it corresponds to the "pure" ability of the trading volume to forecast stock returns, as reported by Gervais, Kaniel, and Mingelgrin (2001) and Stein and Baker (2003). The second hypothesis postulates that the lagged trading volume has no impact on the volatility of the stock market returns. By testing this hypothesis we study the validity of the "information flow" hypothesis which suggests that trading volume might affect the variance of the stock returns. Finally, under H3 the lagged trading volume is postulated to have no impact on the conditional autocovariance of the stock market returns. By testing this hypothesis we test the class of models which relate the trading volume to the magnitude of the reversals or momentum in the stock returns. This class of models includes, among others, the ones proposed by Campbell *et al.* (1993) and Wang (1994) and implies that the lagged trading volume should have a statistically significant impact on the conditional autocovariance and autocorrelation dynamics of the stock returns, and, thus, is an important factor in forecasting whether stock returns will continue or revert during the following trading period.

Next, we formulate hypotheses for the volatility-returns relationship. Let h_t be the variance of the stock market returns at time $t+1$, conditional on the information available at time t. We consider the following null hypotheses

$$\mathbf{H4}: \quad \frac{\partial E(r_{t+1} \,|h_t)}{\partial h_t} = 0$$

$$\mathbf{H5}: \quad \frac{\partial Cov(r_{t+1}, r_t \,|h_t)}{\partial h_t} = 0$$

Hypothesis number four postulates that there is no causal effect of the stock return variance on the expected return. By testing this hypothesis we test the basic mean-variance version of the risk-return trade off. Taking as a proxy for h_t the volatility estimates from GARCH-type models, testing this hypothesis has a straightforward interpretation of a non-parametric test for the presence of GARCH-in-mean effects, which takes into account the potential non-linear dependence of the risk premium on the level of the volatility. Hypothesis H5 postulates that the stock market volatility has no causal effect on the autocovariance of the stock market returns. This hypothesis corresponds to the "feedback trading" model of Sentana and Wadhwani (1992) which relates the magnitude of the stock return reversal to the level of the volatility. Again, taking GARCH-type estimates as a proxy for h_t, this test can be interpreted as testing for the presence of a GARCH-in-autocorrelation effect.

4.5.2 Multiple stock markets: cross-listed securities

Shifting from a single to a multiple market setting adds a number of new dimensions to the role of the trading volume and the volatility in the stock return dynamics. First, when the same security is traded at more than one location, the price discovery process is likely to occur at both markets, and the relative share of each trading location in the former is potentially related to the informative role of the trading volume on *both* markets. In other words, if the trading volume provides additional information to the investors, we might expect the latter to have a significant impact on the speed of adjustment of the cross-listed securities to the "equilibrium" or "intrinsic" value. Next, when the trading locations have overlapping trading hours, the trading volume can potentially play a significant role in the comovements between the stock markets, and, in particular, can have a significant impact on the common factor sensitivities. For instance, if investors tend to underreact to the news revealed during the trading period t, and if the trading volume conveys information in addition to the information implicit in stock prices, then, following a period with high trading volume, we would expect the risk factor sensitivities to increase at period $t+1$. Alternatively, as argued by Gagnon and Karolyi (2003), if the trading volume is a signal of the high share of liquidity traders, then, following the period of high trading volume, one would expect to see less comovement between the markets.

Denote by $r_{US,t}$, $r_{CAN,t}$, $p_{US,t}$, and $p_{CAN,t}$ the close-to-close log-returns and the log-price levels of the cross-listed shares on the US and Canadian markets, respectively. Similarly, let $v_{US,t}$ and $v_{CAN,t}$ denote the trading volume on each of these trading locations. Also, denote by $\xi_t =, p_{US,t} - p_{CAN,t}$ the error correction term, and by $\Delta SP_t(\Delta TSX_t)$ the close-to-close log returns on the US (Canadian) stock market indices. Then the following null hypotheses will be tested

$$\textbf{H6}: \quad \frac{\partial E(r_{i,t+1} \,|v_{j,t})}{\partial v_{j,t}} = 0$$

$$\textbf{H7}: \quad \frac{\partial Var(r_{i,t+1} \,|v_{j,t})}{\partial v_{j,t}} = 0$$

$$\textbf{H8}: \quad \frac{\partial Cov(r_{i,t+1}, \xi_t \,|v_{j,t})}{\partial v_{j,t}} = 0$$

$$\textbf{H9}: \quad \frac{\partial Cov(r_{i,t+1}, \Delta SP_t \,|v_{j,t})}{\partial v_{j,t}} = 0$$

$$\textbf{H10}: \quad \frac{\partial Cov(r_{i,t+1}, \Delta TSX_t \,|v_{j,t})}{\partial v_{j,t}} = 0$$

for $i, j = US, CAN$. The first two hypotheses are similar to those defined in a single market setup. An important difference, however, is that since the security is traded on multiple locations, we test the predictive power of the trading volume on each market. Next, we test whether the lagged trading volume has a significant impact on the price discovery process. As defined by Schreiber and Schwartz (1986), the price discovery is the "process by which markets attempt to find equilibrium prices." In this context, assuming that prices are set such that arbitrage opportunities are absent, prices on both domestic and foreign markets are cointegrated with cointegrating vector $[1, -1]$, $\xi_t = p_{US,t} - p_{CAN,t}$ will be the deviation from the long-run equilibrium, and the dynamics of the price discovery process will be related to the dynamics of the error-correction process, that is, the dynamics of the speed of adjustment on each market (see, for instance, Harris *et al.*, 1995)[1]. Therefore, we study the impact of the lagged trading volume on the price discovery process by testing whether the latter significantly affects the conditional covariance between the stock return on each market and the error correction term, i.e., whether the speed of adjustment on each market depends on the lagged trading volume. Finally, we study the role of the trading volume in the comovement between the stock markets, which, as we hypothesize here, should result in a significant effect of the trading volume on the conditional stock market betas (hypotheses 9 and 10).

4.6 Empirical Findings

In this section we present our testing and estimation results. We start with studying the role of trading volume and volatility in the dynamics of the individual stock markets return. First,

[1] Formal unit root tests, such as the Augmented Dickey-Fuller and Phillips-Perron indicate that the difference between the domestic and foreign log-prices is stationary for all the firms included in our sample. We do not report the results for the sake of saving the space, but the results are available upon request from the corresponding author.

we present and discuss the results of the semi-nonparametric tests applied for the individual stock markets data in subsection 4.6.1. Next, we compare our results with the results of the parametric analysis which are presented in the subsection 4.6.2. Next, we turn to the multiple markets framework. In subsection 4.6.3 we analyse the role of trading volume and volatilty within the semi-nonparametric framework for the cross-listed securities. Finally, in section 4.6.4 we compare the results from the previous subsection with the results of parametric analysis.

4.6.1 Individual Stock Markets- Semi-nonparametric Analysis

We start with analyzing the semi-nonparametric estimation results by testing the joint significance of the FFF coefficients. As mentioned above, in case of the trading volume we study the impact of this variable on the conditional mean, variance, and the autocovariance of the stock market returns, while for the stock market volatility we test whether the volatility affects the conditional mean and the autocovariance of the stock market returns.

In the upper panel of Table 5 we present the p-values of the joint Wald test for the trading volume. Starting with the analysis of the impact of the trading volume on the conditional mean, which corresponds to H1, we find a significant evidence of the trading volume affecting the expected stock market returns for the UK and Hong-Kong and also (some marginally) significant evidence for Germany. For the rest of the markets no such evidence could be found. On the contrary, for most of the markets we find strong empirical evidence of the trading volume affecting the variance of the stock market returns, thus, rejecting H2, a finding which provides some preliminary support for the "information flow" hypothesis. A particularly interesting issue, however, is the impact of the trading volume on the conditional autocovariance of the stock market returns. Surprisingly, only in case of the UK we were able to detect the existence of such a link, while for the rest the null cannot be rejected at any reasonable level of significance. We compare our findings with the ones based on the alternative measure of the trading volume, the log-volume demeaned by one-year moving average, as in Campbell *et al.*(1993).[2] No substantial difference was found when testing whether the lagged trading volume has a significant impact on the conditional mean return. The same holds for the conditional variance, with Italy being the

[2] Consistent with their findings the MA demeaned log-volume series does not exhibit any drift, while it exhibits a substantial degree of persistence.

only exception, where the effect of the trading volume turns out to be statistically significant. As for the volume-autocovariance link the results, in general, remain unaltered as well. The only noteworthy difference is that with the MA-demeaned volume we find statistically significant links for both the US and the UK, while for the rest of the markets the null still cannot be rejected.

The weak evidence of the volume-autocovariance link comes in sharp contrast with the numerous studies which report that using the lagged trading volume as an additional filter improves the performance of the contrarian/momentum based investment strategies (see, for instance, Conrad, Hameed, and Niden (1994), among others). Combined with our findings, these results suggest that, though the trading volume may have a significant impact on the magnitude of the stock return reversal, the link between the former and the latter seems to be *indirect*, rather than direct, as suggested by Campbell *et al.* (1993) and Wang (1994). Such an indirect link between the trading volume and the stock return can occur via a volatility-autocorrelation relationship, and, therefore, we turn to the analysis of the stock market volatility and its role in the stock market return dynamics.

In the lower panel of Table 5 we report the p-values for the joint Wald test for the volatility related hypotheses. As a basic volatility measure we choose the EGARCH(1,1) model of Nelson (1991). This model has an important advantage compared to other existing models, since it does not require any restrictions to be imposed on the variance equation parameters and is also reported to yield superior out-of-sample forecasts compared to other models (Pagan and Schwert, 1990). First, we test the null hypothesis that the stock market volatility has no impact on the expected stock market returns, as stated by H4. Our results strongly suggest that such a link does exist, a finding that could be attributed to the usual risk-return trade-off. Next, we turn to the analysis of the autocovariance-volatility dynamics. For the majority of the markets in our sample we find that the volatility has a significant impact on the conditional autocovariance of the stock market returns. In other words, the probability of observing momentum or reversal appears to be different during turbulent and tranquil periods, a finding which appears to be consistent with the predictions of the Sentana and Wadhwani (1992) "feedback trading" model. As with the trading volume we compare our results with those based on the alternative measure of the stock market volatility. We run the same test for the volatility proxy implied by the PARCH(1,1) model. Introduced by Ding *et al.* (1993), this model nests a number of linear GARCH-type models by turning the power coefficient of the volatility into an additional parameter which has to be estimated along with the other parameters. We also try different number of the higher order terms by expanding and reducing the window length of M_n. The results remain virtually the same, supporting the robustness of our findings.

While having an advantage of combining both the parametric and nonparametric features, statistical inference on the FFF coefficients should be conducted with care since their asymptotic distribution depends on the approximation order and the way the latter has been chosen (Gallant and Souza,1991). To bypass this difficulty, following Ivaldi *et al.* (1996), in addition to p-values based on an asymptotic approximation, we also construct confidence intervals for the estimated Wald statistics by performing a bootstrap. For each conditional moment we generate 2000 samples by randomly drawing with replacement the dependent variable (the raw return for the conditional mean, the conditionally demeaned squared return for the variance, etc.), and the conditioning variable (the volume or the volatility measure). For each sample we calculate the value of the Wald statistic and by that procedure we create the empirical distribution of the latter under the null that no relation between the trading volume/volatility and the conditional moments exists. The resulting p-values are presented next to the asymptotic approximation based ones in the upper panel of Table 5 for the hypotheses H1-H3 and in the lower panel of Table 5 for the hypotheses H4-H5. Interestingly, an overall impression is that for all the tests under consideration the critical values implied by the bootstrap procedure are somewhat lower than the standard χ^2 based ones. However, we do not find any substantial dispersion based on either of the two approaches. The only exception are France and Germany, where in case of using the bootstrap-based critical values the link between the return autocovariance and the lagged trading volume turns out to be statistically significant.

To summarize our intermediate findings, the results of the semi-non parametric analysis suggest that

a The lagged trading volume significantly affects the volatility of the stock market returns, a finding which is consistent with the "information flow" hypothesis.

b The stock market volatility significantly affects the autocovariance of the stock market returns, supporting the "feedback trading" hypothesis of Sentana and Wadhwani (1992).

c Some limited evidence of the lagged trading volume affecting the autocovariance of the stock market returns has been found, consistent with the predictions of the Campbell *et al.* (1993) and Wang (1994) models.

Table 5: FFF analysis

Trading volume

H_0	US	UK	Canada	Japan	Italy
$\frac{\partial E(r_{t+1}\|v_t)}{\partial v_t}=0$	0.38/0.37	0.03/0.03	0.62/0.61	0.43/0.42	0.17/0.17
$\frac{\partial Var(r_{t+1}\|v_t)}{\partial v_t}=0$	0.000/0.000	0.000/0.000	0.48/0.33	0.37/0.27	0.25/0.19
$\frac{\partial Cov(r_{t+1},r_t\|v_t)}{\partial v_t}=0$	0.35/0.11	0.002/0.02	0.86/0.22	0.85/0.59	0.98/0.93
	Netherlands	Hong-Kong	Germany	France	Australia
$\frac{\partial E(r_{t+1}\|v_t)}{\partial v_t}=0$	0.51/0.48	0.008/0.03	0.1/0.09	0.16/0.17	0.85/0.87
$\frac{\partial Var(r_{t+1}\|v_t)}{\partial v_t}=0$	0.000/0.01	0.004/0.03	0.000/0.002	0.000/0.005	0.89/0.18
$\frac{\partial Cov(r_{t+1},r_t\|v_t)}{\partial v_t}=0$	0.36/0.24	0.84/0.63	0.33/0.03	0.89/0.03	0.96/0.83

Volatility

H_0	US	UK	Canada	Japan	Italy
$\frac{\partial E(r_{t+1}\|h_t)}{\partial h_t}=0$	0.000/0.000	0.18/0.19	0.002/0.01	0.001/0.005	0.001/0.003
$\frac{\partial Cov(r_{t+1},r_t\|h_t)}{\partial h_t}=0$	0.000/0.000	0.04/0.07	0.27/0.05	0.003/0.72	0.000/0.01
	Netherlands	Hong-Kong	Germany	France	Australia
$\frac{\partial E(r_{t+1}\|h_t)}{\partial h_t}=0$	0.002/0.004	0.000/0.001	0.01/0.02	0.04/0.05	0.09/0.06
$\frac{\partial Cov(r_{t+1},r_t\|h_t)}{\partial h_t}=0$	0.000/0.01	0.000/0.003	0.000/0.003	0.16/0.004	0.03/0.05

Estimated equation: $\hat{m}(x) = a_n + b_n x + c_n x^2 + \sum_{l=1}^{\frac{M_n}{2}} (\varphi_{l,n} \cos(lx) + \phi_{l,n} \sin(l,x))$

For each market and for each conditional moment we test the null that $\frac{\partial m(x)}{\partial x} = 0$

The numbers are asymptotic (at the LHS) and bootstrap based (at the RHS) p-values of the Wald statistic of $H_0 : b = c = \varphi_l = \phi_l = 0$ for $1 \leq l \leq \frac{M_n}{2}$

These findings suggest that for the purpose of further analysis it seems reasonable to separate the potential impact of the trading volume on the dynamics of the stock market returns from the effects of the stock market volatility on the latter. Thus, we turn now to a parametric analysis.

4.6.2 Individual Stock Markets - Parametric Analysis

In this section we study the role of the trading volume and the volatility in the stock returns dynamics within a parametric framework. For each market we estimate the following model

$$r_{t+1} = \mu_0 + \mu_1 \widetilde{v}_t + \mu_2 h_t^{0.5} + \rho_t r_t + h_t^{0.5} z_{t+1}$$

$$\rho_t = \rho_0 + \rho_1 \widetilde{v}_t + \rho_2 \widetilde{v}_t^2 + \rho_3 h_t^{0.5}$$

$$\ln(h_t) = \omega + \alpha(|z_t| - E\,|z_t| + \gamma z_t) + \beta \ln(h_{t-1}) + \theta_1 \widetilde{v}_t + \theta_2 \widetilde{v}_t^2$$

$$z_{t+1} \overset{iid}{\sim} GED(\eta)$$

In this specification we allow the lagged trading volume $\widetilde{v}$ (de-trended, as discussed in the previous sections) to have both direct and indirect effects on the expected return of the stock market index. The direct, or "pure" causal effect, of the trading volume is measured by the parameter μ_1 and allows for a volume-return causal effect as reported by Gervais *et al.* (2001) and Baker and Stein (2004). The indirect effect, on the other hand, allows the trading volume to affect the expected stock market returns via the autocorrelation coefficient, as predicted by Campbell *et al.*(1993) and Wang (1994), and is measured by the parameters ρ_1 and ρ_2. In addition, the trading volume is allowed to affect the volatility of the stock market returns via the parameters θ_1 and θ_2, to allow for "information flow" related effects. Also, we allow for the impact of the stock market volatility on the autocorrelation as predicted by the "positive feedback trading" model of Sentana and Wadhwani (1992). We model the volatility as an EGARCH(1,1) process, having as important advantage that it does not require to impose non-negativity constraints on θ_1 and θ_2, and, thus, no *a priori* assumption regarding the sign of the trading volume-volatility relationship is required. This formulation is flexible enough to nest a number of important models. In particular, the Campbell *et al.* (1993) and Wang (1994) models are obtained by setting $\mu_1, \mu_2, \rho_3, \theta_1$, and θ_2 equal to zero, while by setting $(\mu_1, \rho_1, \rho_2, \theta_1, \theta_2)$ equal to zero this model boils down to a version of the Sentana and Wadhwani (1992) "feedback trading" model. Numerous studies suggest that even after controlling for GARCH effects, stock market returns still exhibit excessive kurtosis and propose to use fat-tailed distributions instead of the Gaussian one, such as the Generalized Error (Nelson,1991) or Student-t distributions (Diebold,1998). In this study z_t is assumed to follow a Generalize Error Distribution (GED) with constant parameter η. For $\eta = 2$ GED boils down to the Normal distribution, while for $\eta < 2$ normalized returns exhibit excessive kurtosis.

Maximum likelihood estimates of the mean and variance dynamics are presented in Tables 6 and 7, respectively. For all the markets the conditional variance of the stock market returns exhibit a high degree of persistence, consistent with other related studies. Also, for all the markets the volatility is negatively correlated with the lagged stock returns, a finding, that can be attributed to the "leverage effect". For all the markets the estimate of η is significantly smaller than 2, indicating that even after controlling for GARCH effects the returns still reflect some leptokurtosis.

Turning next to the analysis of the impact of the trading volume and volatility on the stock return dynamics, a number of interesting findings can be mentioned. First, consistent with the results of the semi-nonparametric analysis, the trading volume does seem to provide some information regarding the direction of the stock market returns, a finding which also supports the results of Chen, Firth, and Rui (2001) with the coefficient μ_1 being both statistically and economically significant for five out of the ten markets in our sample. However, the impact of the lagged trading volume on the expected stock market returns does not seem to have any consistent pattern. While for the US, UK, and the Netherlands an increase in trading volume seems to lead to a subsequent decline in the stock market value, a finding which is consistent with predictions of the Baker and Stein (2004) model, for other markets, such as Italy and Germany, the impact of the trading volume on the expected stock market returns shows an opposite sign, which is more consistent with the "visibility" hypothesis of Gervais *et al.* (2001). As for the GARCH-in-mean coefficients, in general, a positive sign of μ_2 is consistent with a risk-return trade-off, but only in case of the US market the stock market volatility has a statistically significant power to forecast future stock returns, a finding, that comes in sharp contrast with the results of the FFF based test. Likely, this suggests that after controlling for a "GARCH-in-autocorrelation" effect the GARCH-in-mean effect becomes insignificant.

Next, we study the impact of the trading volume and the volatility on the autocorrelation between the stock market returns (hypotheses H3 and H5). Supporting the results of the FFF based analysis, the evidence of the trading volume having any *direct* effect on the autocorrelation of the stock market returns as in the Campbell *et al.*(1993) and Wang (1994) models is very weak. Though for some markets, consistent with the above mentioned model (Campbell *et al.*, 1993) the estimate of ρ_1 shows a negative sign, it still lacks statistical significance, with France being the only exception. Turning next to the impact of the stock market volatility on the autocorrelation dynamics, we find that in contrast to the trading volume the "GARCH-in-autocorrelation" effect is both statistically and economically significant for the majority of the stock markets in our sample. More specifically, consistent with the predictions of Sentana and Wadhwani (1992), an increase in the stock market volatility increases the likelihood of observing reversals in the stock market returns, with the estimate of ρ_3 being negative and statistically significant. Still, however, the lagged trading volume seems to have an *indirect* effect on the magnitude of the stock market return reversal via the stock market volatility. For the majority of stock markets, consistent with the results of FFF based tests, we find that the lagged trading volume significantly affects the stock market volatility. More specifically, an increase in the trading volume seems to lead to a higher market volatility, consistent with models which relate the trading volume to the information flow. Combining these results, our findings suggest that in the dynamics of the stock market return reversal mechanism the trading volume plays a secondary, although important, role, while the leading source of changes in the stock market return autocorrelation seems to be the stock market volatility.

To provide some visual impression on the dynamics of the stock market return reversal and volatility, we plot the conditional autocorrelation ρ_t and the conditional volatility h_t implied by the parametric model discussed above. We present the results for the three largest developed markets, namely the US, UK, and Japan, and for the Hong-Kong stock exchange, which is considered to be the largest among the emerging stock markets in Figures 4.1 and Figures 4.2. A general impression is that, though in our model specification the trading volume was allowed to have both a direct and an indirect (via the volatility) effect on the autocorrelation dynamics, its direct effect appears to be negligible compared to the indirect one via the volatility, a finding which supports the results of both the FFF based and parametric analysis. The impact of the volatility on the autocorrelation dynamics is especially pronounced in case of the US and UK markets, where the former is virtually the mirror image of the latter. A number of interesting observations arises from the analysis of the autocorrelation histogram. First, it appears that the major share of the autocorrelation distribution mass lies in the positive range. This finding is consistent with numerous studies reporting daily and intradaily returns, exhibiting an *unconditional* positive serial correlation. It also appears to be negatively skewed, which can be due to both a statistically and an economically significant leverage effect in the volatility dynamics. However, taking into account both the direct effect of the positive feedback trading strategies and the indirect effect of trading volume via the volatility, we find changes, not only in the magnitude, but also in the sign of the stock market return autocorrelation. For instance, taking a look at the dynamics of the US and UK stock market serial correlation, it appears that, starting from the middle of 1997, the latter gradually turns from being moderately positive to substantially negative with peaks around 1999-2000, a finding which can be attributed to the collapse of the "dot.com" bubble. There also is an additional peak around 2002, which is more pronounced for the US market, and which can be attributed to the series of corporate scandals around that period, followed by sharp declines in the stock market value on the one hand and high market turbulence on the other hand. For the Hong-Kong stock market the dynamics of the serial correlation is characterized by a substantially negative serial correlation and a high volatility around the period of mid-1997-mid 1998, that is, the period of a severe currency and stock market crisis, known as the "Asian Flue". The conditional autocorrelation of the Japanese stock market, on the other hand, as well as the variance of the latter, appears to be highly volatile during the whole time-span of our study. Overall, these findings suggest the importance of accounting both for feedback trading and volume-"information flow" related effects in the dynamics of the stock market returns.

For now we studied the role of the trading volume and volatility in a single market setup. Turning to a multiple market setup adds a number of interesting and important dimensions to the trading volume-volatility-return relation, as discussed in a previous section. Thus, in the following subsections we study the relation between the trading volume, volatility and the stock returns for the cross-listed securities.

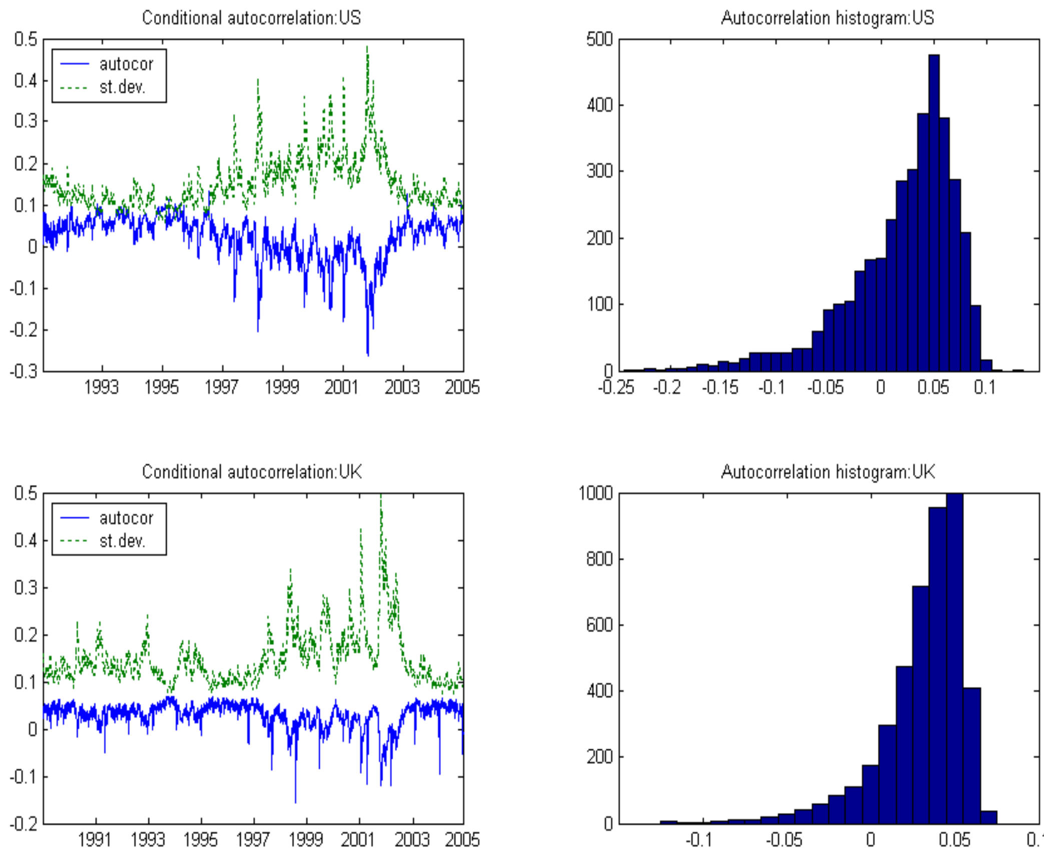

Figure 4-1: Volatility and autocorrelation dynamics: US and UK markets

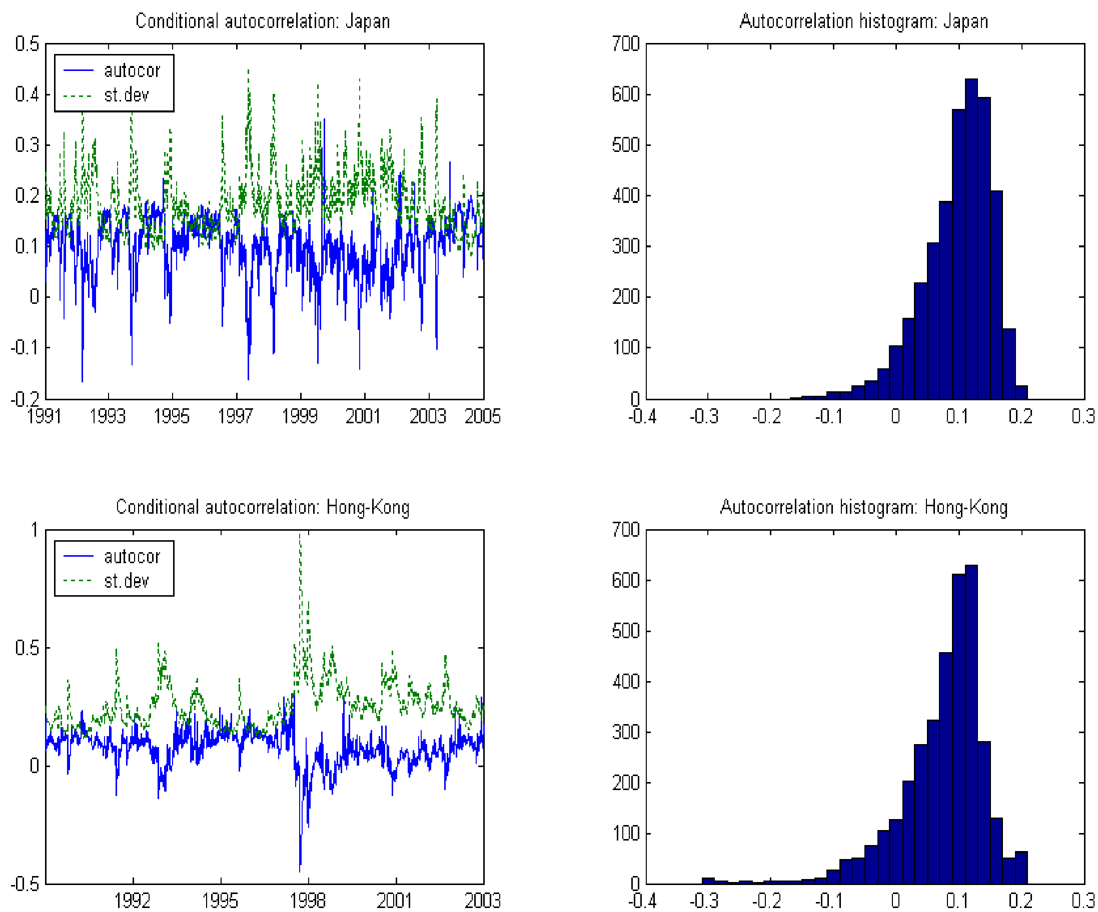

Figure 4-2: Volatility and autocorrelation dynamics: Japan and Hong-Kong markets

Table 6: Trading volume and volatility-mean dynamics

	US	UK	Canada	Japan	Italy
μ_0	-0.0008^{**} (0.0004)	-0.0003 (0.0004)	0.0004 (0.0003)	-0.0012^{**} (0.0006)	$-6 \cdot 10^{-5}$ (0.00045)
μ_1	-0.0015^{**} (0.0005)	-0.0011^{**} (0.0004)	0.0002 (0.0003)	0.0004 (0.0005)	0.0007^{**} (0.0003)
μ_2	0.14^{**} (0.05)	0.07 (0.052)	0.0021 (0.045)	0.09 (0.056)	0.04 (0.045)
ρ_0	0.155^{**} (0.05)	0.01 (0.043)	0.32^{**} (0.038)	0.27^{**} (0.06)	0.19^{**} (0.049)
ρ_1	0.023 (0.07)	0.021 (0.043)	-0.006 (0.056)	-0.003 (0.045)	-0.034 (0.036)
ρ_2	0.039 (0.08)	-0.015 (0.045)	-0.061 (0.084)	0.024 (0.049)	0.0035 (0.037)
ρ_3	-14.63^{**} (4.49)	-7.31^{**} (4.14)	-19.16^{**} (3.97)	-15.26^{**} (4.37)	-9.71^{**} (3.55)
	Netherlands	Hong-Kong	Germany	France	Australia
μ_0	0.0004 (0.0003)	0.0005 (0.0006)	0.0002 (0.0004)	-0.0009 (0.0007)	0.0003 (0.0005)
μ_1	-0.0004^{**} (0.0002)	-0.0006 (0.0004)	0.0004^{**} (0.00013)	-0.0007 (0.00049)	0.0001 (0.0005)
μ_2	0.013 (0.039)	-0.016 (0.052)	0.043 (0.042)	0.097 (0.064)	0.012 (0.095)
ρ_0	0.11^{**} (0.031)	0.22^{**} (0.039)	0.102^{**} (0.038)	0.041 (0.056)	0.098 (0.077)
ρ_1	0.021 (0.033)	-0.031 (0.034)	-0.028 (0.018)	-0.096^{**} (0.05)	0.038^{**} (0.091)
ρ_2	0.0012 (0.0087)	0.079^{**} (0.038)	0.011 (0.016)	0.009 (0.068)	-0.058 (0.12)
ρ_3	-8.21^{**} (2.75)	-10.99^{**} (2.2)	-6.07^{**} (3.14)	-1.55 (3.92)	-11.98 (11.05)

Model: $r_{t+1} = \mu_0 + \mu_1 \widetilde{v}_t + \mu_2 h_{t+1}^{0.5} + (\rho_0 + \rho_1 \widetilde{v}_t + \rho_2 \widetilde{v}_t^2 + \rho_3 h_{t+1}^{0.5}) r_t + h_{t+1}^{0.5} z_{t+1}$

$$\ln(h_{t+1}) = \omega + \alpha(|z_t| - E|z_t| + \gamma z_t) + \beta \ln(h_t) + \theta_1 \widetilde{v}_t + \theta_2 \widetilde{v}_t^2$$

$$z_t \overset{iid}{\sim} GED(\eta)$$

*(**) denotes significance at 10 (5) %

Table 7: Trading volume and volatility-volatility dynamics

	US	UK	Canada	Japan	Italy
ω	-0.225^{**} (0.039)	-0.165^{**} (0.032)	-0.122^{**} (0.026)	-0.348^{**} (0.063)	-0.16^{**} (0.036)
α	0.113^{**} (0.014)	0.114^{**} (0.014)	0.146^{**} (0.014)	0.187^{**} (0.021)	0.165^{**} (0.015)
β	0.976^{**} (0.004)	0.983^{**} (0.003)	0.988^{**} (0.0026)	0.961^{**} (0.007)	0.983^{**} (0.004)
γ	-0.09^{**} (0.009)	-0.058^{**} (0.008)	-0.051^{**} (0.01)	-0.099^{**} (0.012)	-0.048^{**} (0.0086)
θ_1	0.032^{**} (0.012)	0.017^{**} (0.008)	0.014 (0.013)	0.03^{**} (0.015)	0.0002^{**} (0.058)
θ_2	0.031 (0.023)	0.032^{**} (0.013)	0.036 (0.031)	-0.0064 (0.026)	0.0091 (0.0069)
η	1.48^{**} (0.038)	1.72^{**} (0.04)	1.44^{**} (0.03)	1.43^{**} (0.04)	1.49^{**} (0.039)
Log-ld	12534.4	14785.52	13031.36	11432.54	11627.99

	Netherlands	Hong-Kong	Germany	France	Australia
ω	-0.18^{**} (0.029)	-0.153^{**} (0.04)	-0.192^{**} (0.03)	-0.126^{**} (0.033)	-0.341^{**} (0.098)
α	0.157^{**} (0.015)	0.134^{**} (0.017)	0.124^{**} (0.013)	0.116^{**} (0.014)	0.07^{**} (0.021)
β	0.981^{**} (0.003)	0.982^{**} (0.004)	0.98^{**} (0.0034)	0.986^{**} (0.004)	0.967^{**} (0.008)
γ	-0.056^{**} (0.007)	-0.065^{**} (0.0097)	-0.06^{**} (0.009)	-0.061^{**} (0.0088)	-0.142^{**} (0.017)
θ_1	0.022^{**} (0.006)	0.012^{**} (0.0060	0.0031 (0.0025)	-0.003 (0.007)	0.073^{**} (0.035)
θ_2	0.0044 (0.0034)	0.0068 (0.0077)	0.0054^{**} (0.0027)	0.008 (0.018)	0.063 (0.068)
η	1.49^{**} (0.027)	1.36^{**} (0.03)	1.38^{**} (0.018)	1.74^{**} (0.061)	1.56^{**} (0.058)
Log-ld	16728.42	10010.31	14385.4	9869.57	5344.01

Model: $r_{t+1} = \mu_0 + \mu_1 \widetilde{v}_t + \mu_2 h_{t+1}^{0.5} + (\rho_0 + \rho_1 \widetilde{v}_t + \rho_2 \widetilde{v}_t^2 + \rho_3 h_{t+1}^{0.5}) r_t + h_{t+1}^{0.5} z_{t+1}$

$$\ln(h_{t+1}) = \omega + \alpha(|z_t| - E|z_t| + \gamma z_t) + \beta \ln(h_t) + \theta_1 \widetilde{v}_t + \theta_2 \widetilde{v}_t^2$$

$$z_t \overset{iid}{\sim} GED(\eta)$$

*(**) denotes significance at 10 (5) %

4.6.3 Cross-listed Securities - a Semi-nonparametric Analysis

In the following subsections we extend the analysis of the role of the trading volume and volatility in the dynamics of the stock markets to a multiple-market setup. More specifically, we conduct our analysis based on a comprehensive sample of Canadian firms whose shares are listed both on the Toronto and the New-York stock exchanges. Since these firms' shares are simultaneously traded on both domestic and foreign markets, an interesting issue is not only to study the relationship between the information flow mechanism, the trading volume, and the volatility within each market, but also to compare their relative impacts on the dynamics of the stock returns between the markets.

We start with the results of the semi-nonparametric analysis. In Table 8 we present the results of the FFF based tests of the hypotheses H6-H10, as described in Section 4. For each cross-listed firm included in our sample, we test five hypotheses listed in the first column of Table 8, based both on the asymptotic and the bootstrap-based approximations of the Wald statistic. We do not present individual results for each firm but, instead, for each hypothesis we present an overall fraction of firms out of the total sample for which the null has been rejected at a 10 percent level of significance. We refer to this fraction as a "rejection ratio." We decide to reject an "overall" specific null if an overall fraction of firms for which the null is rejected significantly exceeds 0.1, that is, the size level of the test for the individual firm. In other words, we decide to reject a specific null hypothesis if the fraction of firms for which this specific null has been rejected significantly exceeds the one that can be attributed to the Type 1 error.

Table 8: Cross-listed securities-FFF analysis

H_0	NYSE/AMEX		TSE	
	v_{US}	v_{CAN}	v_{US}	v_{CAN}
$\frac{\partial E(r_{i,t+1}\vert v_{j,t})}{\partial v_{j,t}} = 0$	0.15/0.15	0.19**/0.18**	0.2**/0.19**	0.21**/0.13
$\frac{\partial Var(r_{i,t+1}\vert v_{j,t})}{\partial v_{j,t}} = 0$	0.44**/0.44**	0.36**/0.31	0.43**/0.43**	0.17*/0.32**
$\frac{\partial Cov(r_{i,t+1},\xi_t\vert v_{j,t})}{\partial v_{j,t}} = 0$	0.46**/0.35**	0.25**/0.2**	0.28**0.22**	0.21**/0.15
$\frac{\partial Cov(r_{i,t+1},\Delta SP_t\vert v_{j,t})}{\partial v_{j,t}} = 0$	0.25**/0.25**	0.23**/0.14	0.29**/0.18*	0.18*/0.13
$\frac{\partial Cov(r_{i,t+1},\Delta TSX_t\vert v_{j,t})}{\partial v_{j,t}} = 0$	0.32**/0.28**	0.18*/0.14	0.29**/0.28**	0.17*/0.12

Estimated equation: $\hat{m}(x) = a_n + b_n x + c_n x^2 + \sum_{l=1}^{\frac{M_n}{2}} (\varphi_{l,n} \cos(lx) + \phi_{l,n} \sin(l,x))$

For each market and for each conditional moment we test the null that $\frac{\partial m(x)}{\partial x} = 0$

The numbers are asymptotic (at the LHS) and bootstrap based (at the RHS) rejection rates of Wald statistic of $H_0 : b = c = \varphi_l = \phi_l = 0$ for $1 \leq l \leq \frac{M_n}{2}$

We start with the null that the trading volume has no impact on the conditional mean of the stock returns or, in other words, does not help to predict the direction of change of stock prices, which corresponds to hypothesis H6. As can be seen from our results, for both the Canadian and the US trading volume a rejection ratio significantly exceeds 0.1, though the difference is not substantial. Also, the impact of the US trading volume on the conditional mean of the Canadian return lacks statistical significance. On the other hand, for both the TSE and the NYSE/AMEX we find strong evidence of the trading volume affecting the variance of the stock returns, thus, rejecting hypothesis H7. The evidence is especially strong for the US volume where the rejection ratios are 0.44 and 0.43, respectively, i.e., the null is rejected for almost every second firm. Next, we turn to the impact of the trading volume on the price discovery process on both markets, namely the question of whether an increase in the trading volume affects the mechanism of the error correction dynamics (hypothesis H8). For both markets we are able to reject the null that the trading volume does not contribute to the dynamics of the price discovery process, though in case of the Canadian volume affecting the TSE returns, the rejection ratio is somewhat low. Finally, we turn to the impact of the lagged trading volume on the conditional US and Canadian market betas by testing hypotheses H9 and H10. Interestingly, for both markets we find that the trading volume seems to have a statistically significant impact on the sensitivities to the market risk. This finding is particularly interesting since it emphasizes a potential role of the trading volume, not only in the dynamics of a single asset, but also in the comovement between stock prices at different markets. It also suggests that the lagged trading volume can serve as a useful instrument for modeling and estimating the dynamics of the conditional sensitivities to the market risk.

4.6.4 Cross-listed Securities - a Parametric Analysis

To gain some further insight into the volume-volatility-return dynamics we turn next to a parametric analysis. First, we study the role of the trading volume in the mean dynamics of the stock returns. Next, we turn to the impact of the trading volume on the volatility of the stock returns.

Mean Dynamics

We start with specifying the equation of the mean dynamics. For each firm in our sample we estimate the following regression

$$r_{i,t+1} = \mu_{i,0} + \mu_{i,1} v_{US,t} + \mu_{i,2} v_{CAN,t} + \delta_{i,t}\xi_t + \beta_{i,t}^{US}\Delta SP_{t+1} + \beta_{i,t}^{CAN}\Delta TSX_{t+1} + \epsilon_{i,t+1}$$

$$\delta_{i,t} = \delta_{i,0} + \delta_{i,1} v_{US,t} + \delta_{i,2} v_{CAN,t}$$

$$\beta_{i,t}^{US} = \beta_{i,0}^{US} + \beta_{i,1}^{US} v_{US,t}$$

$$\beta_{i,t}^{CAN} = \beta_{i,0}^{CAN} + \beta_{i,1}^{CAN} v_{CAN,t}$$

for $i = US, CAN$. In this regression equation the parameters μ_1 and μ_2 measure the direct impact of the trading volume on the expected returns and δ_1 and δ_2 measure the effect of the trading volume on the dynamics of the price discovery process via the speed of adjustment coefficient δ_t. In addition, we allow the market risk sensitivities $\beta-$s to be time-varying via a time variation in trading volume. To keep the specification parsimonious in terms of modeling the market risk sensitivities, we restrict the impact of the trading volume on its own market beta (that is, the US volume on β^{US} and the Canadian volume on β^{CAN}). The intuition behind this restriction is that if the lagged trading volume does provide information to the investors, it is more likely that it is the trading volume on the US markets that provides additional information to the one implicit in the US stock prices and vice versa. The innovation $\epsilon_{i,t+1}$ is assumed to be mean independent from the regressors.

The estimation results are presented in Table 9, where we report the average least-squares estimates of the regression discussed above. Starting with the direct impact of the trading volume on the expected stock returns, we find that for the stocks traded on the US markets the direct effect of the trading volume is economically and statistically significant for both the US and the Canadian volume, with estimates of μ_1 and μ_2 being highly statistically significant. The results appear to be similar for the Canadian sample, though for the US trading volume the estimate of μ_1, being economically significant, lacks statistical significance. An interesting observation, however, is that for both the US and Canadian samples the estimates of μ_1 and μ_2 have opposite signs, while being of the same magnitude (in absolute value). A formal test of the hypothesis $\mu_1 = -\mu_2$ indicates that the null cannot be rejected at any reasonable significance level with p- values equal to 0.48 and 0.62 for the US and Canadian samples, respectively, suggesting that in the multiple market setting it is the relative rather than the absolute trading volume that affects the expected stock returns.

This conjecture is strengthened when we examine the impact of the trading volume on the price discovery mechanism, namely, the estimates of δ_1 and δ_2. For both the US and Canadian samples the estimates of δ_1 and δ_2 are positive and negative, respectively, and highly statistically significant. As in case with μ_1 and μ_2 formal tests of the hypothesis $\delta_1 = -\delta_2$ suggest that the null cannot be rejected at any legitimate significance level. Again, it appears that it is the *relative* rather than absolute volume that affects the error-correction and thus the price discovery mechanism. More specifically, for the Canadian sample an increase in the relative US volume, on average, significantly increases the speed of adjustment, while adversely affecting the latter for the sample of the US shares, with δ_1 being positive and statistically significant. The results are opposite when we examine the impact of the relative Canadian volume on the error-correction dynamics, where the estimate of δ_2 appears to be significantly negative. The underlying intuition is that when the trade occurs on more that one market, investors tend to extract the information both from the trading volume on the domestic and foreign markets, and, therefore, it is the *relative* rather than the absolute volume that determines at which market the lion's share of the price discovery occurs or, modifying the definition of Garbade and Silber (1979), which market emerges as the *conditionally* dominant one. Our results suggest that the relative trading volume serves as a useful indicator for this purpose. Note that when the trade is symmetrically allocated (that is, when the difference between the trading volumes on both markets is zero) the price discovery process almost breaks even between both markets with the estimates of $\delta_{US,0}$ and $\delta_{CAN,0}$ being close one to one another in magnitude.[3] As the US trading volume increases relatively to the Canadian trading volume, that is, as the trade during the previous trading day becomes more and more concentrated at the US markets, the speed of adjustment coefficients are increasing for the Canadian market and decreasing for the US market, implying that the price discovery process becomes more concentrated at the US market, turning the latter into the informationally dominant one.

[3] Note that an increase in the speed of adjustment for the US sample means that $\delta_{US,t}$ becomes more **negative**.

Table 9: Cross-listed securities: mean dynamics

	NYSE/AMEX		TSE	
	Coef.	S.Error	Coef.	S.Error
μ_0	0.0032	(0.0038)	0.0097	(0.013)
μ_1	-0.0013*	(0.00076)	-0.0016	(0.0013)
μ_2	0.0008**	(0.0002)	0.0009**	(0.0002)
δ_0	-0.625**	(0.129)	0.332**	(0.114)
δ_1	0.072**	(0.022)	0.06**	(0.021)
δ_2	-0.041**	(0.017)	-0.042**	(0.017)
β_0^{US}	-0.39**	(0.117)	-0.375**	(0.114)
β_1^{US}	0.073**	(0.019)	0.061**	(0.019)
β_0^{CAN}	0.264*	(0.14)	0.26*	(0.14)
β_1^{CAN}	0.078**	(0.024)	0.088**	(0.022)
$\bar{R}^2_{adj}$	0.14		0.13	

Model: $r_{i,t+1}= \mu_{i,0}+\mu_{i,1}v_{US,t}+\mu_{i,2}v_{CAN,t}+\delta_{i,t}\xi_t$

$$+\beta_{i,t}^{US}\Delta SP_{t+1}+\beta_{i,t}^{CAN}\Delta TSX_{t+1}+\epsilon_{i,t+1}$$

$$\delta_{i,t}= \delta_{i,0}+\delta_{i,1}v_{US,t}+\delta_{i,2}v_{CAN,t}$$

$$\beta_{i,t}^{US}= \beta_{i,0}^{US}+\beta_{i,1}^{US}v_{US,t}$$

$$\beta_{i,t}^{CAN}= \beta_{i,0}^{CAN}+\beta_{i,1}^{CAN}v_{CAN,t}$$

$^{*(**)}$ denotes significance at 10 (5) % significance

Next, we turn to the role of the trading volume in the stock market comovements, namely the estimates of the conditional betas. Here, the results are particularly intriguing. Our findings suggest that the stock market "betas" exhibit a substantial degree of time-variation, depending on the trading activity at both markets. More specifically, we find, for both the US and Canadian samples, that following days with a high trading activity, both the US and Canadian market betas are significantly increasing. This finding, which −as discussed before− is consistent with the informative role of the trading volume, suggests that following days with a high trading activity the systemic risk tends to increase, implying that the trading volume may serve as a useful instrument in the conditional risk modeling.

Our finding that market risk sensitivities of the individual assets are positively related to the trading volume also sheds some new light on the results of Gervais *et al.* (2001) who find that, following days with a high trading volume, stocks tend to exhibit positive excess returns. They attribute this finding to the "visibility" phenomenon and argue that, following days with a high trading activity, stocks become more "visible" to the investors. An expansion of the investors' base along with short-sale restrictions, they argue, leads to subsequent positive returns. Our findings, however, suggest a different interpretation of their results. Since the market risk of the individual securities appears to be positively related to the lagged trading volume, positive returns following the days with a high market activity can be a compensation for an increase in the market risk.

We conduct a number of robustness checks. First, we augment our regressions with first-order lags of the Canadian and US returns along with lagged returns on the corresponding stock market indices. The main results remain virtually unaltered. Interestingly, we find that both the Canadian and the US shares seem to exhibit significant underreaction to the news from the TSE, with the estimated coefficients of the Canadian stock market lags being positive and statistically significant. Next, we estimate the same regression with the log-de-trended, instead of the raw log-volume, with no substantial change in the results. Finally, in order to take into account possible auto- and cross-autocorrelations in the trading volume,[4] we replace the raw log-volume by the estimated residuals from a Vector Autoregression with two lags. The only substantial difference is that the coefficient of the trading volume-TSX interaction term turns out to be statistically insignificant though positive. Also, CUSUM stability tests indicate that the coefficients are reasonably stable over time. Overall, our findings appear to be fairly robust to various regression and trading volume specifications.

Volatility Dynamics

Next, we study the relationship between the trading volume and the volatility of the stock returns. As the volatility is considered to be a proxy for the information flow (see, for instance, Chan, Chan, and Karolyi (1991), among others), we start with an analysis of a simple measure

[4] Numerous articles report the trading volume being significantly autocorrelated (for example, Gallant and Tauchen (1992)). Our results support their findings with the VAR yielding an average adjusted R^2 of 0.32 and 0.16 for the US and Canadian trading volume, respectively.

of the unconditional relative market informativeness, as proposed by Lieberman, Ben-Zion, and Hauser (1999). For each pair of cross-listed securities we calculate the ratio of the residual variance from the US and Canadian markets, $\frac{\sigma^2_{\epsilon,US}}{\sigma^2_{\epsilon,CAN}}$,which serves as a proxy to the average information flow on the US and Toronto stock exchanges, respectively. We hypothesize that this measure of the relative market informativeness should be positively related to the US share of trade which we define here as the average daily US volume divided by the average trading volume on both markets. In the upper panel of Table 10 we present some descriptive statistics of this variance ratio measure, both for the whole sample and for the US share of trade-based portfolios which are grouped in ascending order from the firms with the lowest US share (Q1) to those with concentration of trading activity on the US market (Q4). Starting with an overall sample we find that both the mean and the median are close and in case of the mean also insignificantly different from 1, suggesting that the pricing information revealed on one market transfers rapidly to the other. Turning to the US share of the trade-based portfolios we observe that both the mean and median estimates are increasing from the lower to the upper quartiles, though this increase is not monotonous. Nevertheless, consistent with our prior conjecture, we find a positive and statistically significant relationship between the US share of trade and the variance ratio, with Spearman's rho being positive and statistically significant (p -value equal to 0.01).

As a next step we study the volume-volatility relationship in a dynamic context. Multivariate GARCH-type models have been widely used in modeling the mechanism of the information transfer from one market to another (see, for instance, Lin, Engle, and Ito,1994; Koutmous and Booth,1995; and Tse,1999 among others). In order to study the dynamics of the trading volume-volatility relationship following these and other studies, for each firm in our sample we estimate the following bivariate EGARCH model

$$\begin{pmatrix}\epsilon_{1,t+1}\\ \epsilon_{2,t+1}\end{pmatrix}|\Omega_t \sim Dist\left(0,\sum\nolimits_{t+1}\right)$$

$$\sum\nolimits_{t+1} = \begin{bmatrix} h_{1,t+1} & \rho(h_{1,t+1}h_{2,t+1})^{0.5} \\ \rho(h_{1,t+1}h_{2,t+1})^{0.5} & h_{2,t+1} \end{bmatrix}$$

$$\ln(h_{1,t+1}) = \omega_1 + \alpha_1 G_{1,t} + \beta_1 \ln(h_{1,t}) + \delta_1 G_{2,t} + \theta_{1,US} v_{US,t} + \theta_{1,CAN} v_{CAN,t}$$

$$\ln(h_{2,t+1}) = \omega_2 + \alpha_2 G_{2,t} + \beta_2 \ln(h_{2,t}) + \delta_2 G_{1,t} + \theta_{2,US} v_{US,t} + \theta_{2,CAN} v_{CAN,t}$$

$$G_{i,t} = \{|u_{i,t}| - E\,|u_{i,t}| + \gamma_i u_{i,t}\}\,, \quad u_{i,t} = \epsilon_{i,t}/h_{i,t}^{0.5}, \quad i = 1, 2$$

Here, we assume that the conditional covariance matrix of the Canadian and the US stock returns follows a bivariate EGARCH-type process with a constant correlation ρ, as in Bollerslev (1992). The parameters δ_1 and δ_2 measure the cross-market volatility spill-overs, which are also allowed to be sign-dependent via the parameters γ_1 and γ_2. We allow both the US and the Canadian trading volume to effect the variance of the stock returns on both markets via the parameters $(\theta_{1,US}, \theta_{2,US})$ and $(\theta_{1,CAN}, \theta_{2,CAN})$. The parameters of the model are estimated using a Quasi-Maximum Likelihood framework. Due to the relatively large dimension of the parameter vector and the large number of companies, we apply a two-step estimation procedure. First, the estimates of the residuals $\epsilon_{i,t}$ are obtained from the above-mentioned regression. The elements of the variance-covariance matrix are then simultaneously estimated via a standard maximization procedure of the bivariate Gaussian log-likelihood function. Though asymptotically not efficient, under the assumption of a correct mean and variance-covariance matrix specification the estimates are still consistent (Bollerslev and Woolridge,1992) and since we are interested in the average estimates it is consistency that is crucial for our analysis.

The estimation results are presented in the lower panel of Table 10. Instead of presenting the results for each firm, we present the cross-sectional average of the estimates with corresponding cross-sectional standard errors for each parameter of the model.[5]. First, consistent with other studies (Sentana and Wadhwani,1992; Koutmos,1996), we find that the stock return volatility exhibits a substantial degree of persistence, with an average estimate of β close to one, though statistically still different from one. Also, for both markets there is a strong evidence of the different impacts of "bad" and "good" news with the estimate of γ being significantly negative, a finding which can be attributed to a "leverage" effect. It is worth emphasizing the economic significance of the "leverage" effect, which, according to our estimation results, leads to a more than 50% discrepancy between the impact of "good" and "bad" news on the volatility! We also find strong evidence of cross-market volatility spill-overs between the shares listed on the TSE

[5] This approach is valid under the assumption that the time-dimension is of higher order than the cross-sectional dimension. Since in our study the time-span substantially exceeds the number of firms, this assumption does not seem to be too stringent.

and their "twins" listed on the US markets. Interestingly, it appears that the spill-over from the US to the Canadian market is more pronounced than in the opposite direction, though the difference is not statistically significant.

Turning next to the analysis of the trading-volume volatility relationship, the results are particularly intriguing. First, controlling for the impact of both the Canadian and the US trading volume, we find the latter having both a statistically and an economically significant impact on the volatility of stock returns with $\hat{\theta}_{US}$ being highly significant. On the other hand, we find no evidence of the Canadian volume affecting the volatility dynamics, with $\hat{\theta}_{CAN}$ lacking statistical significance for both markets. Curiously, the estimate of θ_{US} is significantly negative, suggesting that, on average, we might expect the stocks to be less volatile following a period of intensive trading on the US markets. This finding comes in contrast to the "information flow" theories which relate both trading volume and volatility to the intensity of the information flow and, thus, predict a positive relationship between the former and the latter. However, since the subject of our analysis are the firms listed and traded simultaneously on both the domestic and the foreign market it seems reasonable to study the impact of the trading volume separately for the firms with a low and a high intensity of the information transfer between the markets. We use the estimate of the cross-market correlation, ρ, as a measure of the intensity of the cross-market information transfer. Interestingly, for both the US and the Canadian markets we find a positive and significant relationship between the impact of the US trading volume on the volatility, that is, θ_{US} and the cross-market correlation ρ. For the US market an estimate of Spearman's rho between these two parameters is 0.24 (p-value 0.01) and is also marginally significant for the Canadian market (rho=0.16 and p-value is 0.1). Further analysis indicates that, while for the low-correlation firms the impact of the trading volume on the volatility is significantly negative, it turns out to be positive for the firms with a high ρ. That is, we find supporting evidence for the "information flow" hypothesis for the firms with an intense cross-border transfer of pricing information. On the other hand, for the firms with a low cross-market correlation it seems that the trading volume is a proxy for the liquidity shocks, leading to a lower variance in the subsequent trading period, rather than to informative trading.

To provide a visual impression on the dynamics of the price-discovery process and the cross-market information flows, we plot the average share of the US market in the price discovery process and the average conditional variance ratio in the upper and lower panels of Figure 4.3, respectively. Here, following the terminology and extending the methodology of Schreiber and Schwartz (1986) and Eun and Sabherwal (2003), we define the *conditional* US share in the price discovery for a specific firm j and period t as $\frac{\delta_{j,CAN,t}}{|\delta_{j,US,t}|+\delta_{j,CAN,t}}$, that is, the share of the adjustment occurring on Canadian market out of the total adjustment occurring on both the US and Canadian markets at period t[6]. This ratio is a natural refinement of the original measure used by Eun and Sabherwal (2003), who assume that the speed of adjustment is constant for both markets, an assumption which is strongly rejected in our study. Therefore, it would be interesting to study the evolution of the price-discovery process over time. As for the conditional variance ratio, we define the latter as $\frac{h_{j,US,t}}{h_{j,CAN,t}}$ for a specific firm i and period t. This measure, which is also a natural refinement of the unconditional variance ratio used by Lieberman, Ben-Zion and Hauser (1999), will allow us to study the relative intensity of the information flows on both domestic and foreign markets and its evolution over time. Since we use different time-periods for different firms, we picked only those with continuous data during the period January 2000-December 2005, and for each period t we calculate a cross-sectional average of the US price discovery shares and the variance ratios of the individual firms. That is, for each period t, we present the average US price discovery share and the average variance ratio, which are calculated as $\frac{1}{N}\sum_{j=1}^{N}\frac{\delta_{j,CAN,t}}{|\delta_{j,US,t}|+\delta_{j,CAN,t}}$ and $\frac{1}{N}\sum_{j=1}^{N}\frac{h_{j,US,t}}{h_{j,CAN,t}}$ with N, the number of firms corresponding to our criterion, being equal to 27.

Starting with the US price discovery share, an inspection of its histogram indicates that during the time-span of our study the US market behaved as a satellite one, with a lion's share of the US share lying below 0.5, a finding which is consistent with other studies which report that the domestic market emerges as the dominant one. However, it also exhibits a substantial degree of time-variation with a minimum share of 0.3 and a maximum around 0.6, suggesting that taking into account the conditional variation in the speed of adjustment during the periods when the trade is concentrated on the US stock exchange, the latter becomes the dominant market. Interestingly, the average US price discovery share exhibits an upward trend, starting from 0.35 and reaching the average level of 0.5. A similar picture unfolds from inspecting the time evolution of the average relative volume, which we define as the cross-sectional average

[6]Note that since $\delta_{US,t}$ is non-positive applying an absolute value operator to $\delta_{US,t}$ is necessary.

of the differences between the US and Canadian trading log-volumes and which is depicted in Figure 4.4. While at the beginning of our sample, trading was heavily concentrated on the Canadian market, over time one can clearly observe the former gradually reallocating from the TSE to the US markets and by the end of 2005 almost breaking even between both the domestic and the foreign market, which corresponds to the price discovery process breaking even between the TSE and the US markets. Turning to the analysis of the average conditional variance ratio, we find it fluctuating around the level one, suggesting that both markets are highly integrated, with highly intensive cross-border information flows in both directions. Interestingly, there is a single peak around the period of March 2000, when the US market plummeted down due to the collapse of the "Internet" bubble and when this market was characterized by an unusually high volatility which also seems to cause the distribution of the variance ratio to be slightly positively skewed.

4.7 Summary and Conclusions

In this paper we study the role of the trading volume and the volatility in the dynamics of the stock markets. In particular, we study the role and the predictive power of the trading volume and the volatility both for the individual national stock markets and for the securities listed on multiple markets. Our analysis is based on both parametric and semi-nonparametric (Flexible Fourier Form) estimation methodologies, which makes our findings robust to potential model specification errors.

For the individual national stock markets our key findings are as follows. First, we find strong evidence of the lagged trading volume affecting the variance of the stock market returns. More specifically, an increase in the trading volume leads to an increase in the stock market variance during the subsequent trading period, a finding which is consistent with the "information flow" hypothesis. Secondly, we find that the stock market return autocorrelation is inversely related to the volatility, a finding which supports the "feedback trading" theory of Sentana and Wadhwani (1992). Third, no negative relation between the lagged trading volume and the autocorrelation, as suggested by Campbell *et al.* (1993) model, has been found. Combining these three findings together, our results suggest that the profitability of volume-filter based contrarian strategies, as reported by Conrad, Hameed, and Niden (1994), can be explained by the combination of the "information flow" and "feedback trading" models, but might not be explained by the trading volume-autocorrelation class of models, such as the Campbell *et al.* (1993) and Wang (1994) models.

We also study the role of the trading volume in a multiple markets context. Based on a comprehensive dataset of Canadian firms listed on both the domestic and the US stock markets we study the role of the trading volume in the price discovery process and in the comovements between the stock markets. We find strong evidence in favor of the lagged trading volume affecting the price discovery process via the speed of adjustment coefficients of the securities. Interestingly, our findings suggest that it is the *relative* rather than the absolute volume that affects the dynamics of the price discovery process. More specifically, we find that an increase in the relative US trading volume leads to a subsequent increase in the share of the price discovery that occurs on the US market and vice-versa, or, borrowing the terms of Garbade and Silber (1979), turns the US market to the dominant one. This finding is consistent with the results of Stickel and Verrecchia (1994) when extended to a multiple market setup, who suggest that investors interpret a high volume as an indication of the informative demand. We also find significant evidence in favor of the trading volume affecting the comovement of the securities' prices between the market via risk factor sensitivities. In particular, we find that following days with a high trading volume the CAPM-betas of the individual securities significantly increase as well. This finding, which we interpret as additional evidence of the informative role of the trading volume, suggests that the "high volume premium" reported by Gervais, Kaniel, and Mingelgrin (2001) can be viewed as a compensation for additional risk.

Our results suggest a number of interesting directions for further research. First, our results seem to indicate that the dominant factor that governs the stock return reversal dynamics is the stock market volatility and not the trading volume. Thus, it seems reasonable to compare the profitability of the contrarian strategies based on the volatility-filters with those based on the trading volume filters. One way to proceed will be to use a volatility/volume weighted version of the zero-investment strategy, proposed by Lo and MacKinlay (1990). Second, it would be interesting to make a distinction between the informative and the non-informative trading periods by looking at the share of the medium-size trades during a particular trading period, following Barclay and Warner (1993), who report that informed traders are concentrated in the medium-size category. If informed trades are indeed characterized by the medium size, the volume-price relationship during days with a high share of the medium-size trades may differ from ones when this share is low. Finally, it would be interesting to study the intraday dynamics of the price discovery process. Numerous studies report the trading volume to follow a "U-shape", which in the context of our study would suggest that the price adjustment process is likely to be rapid at the beginning/end of the trading day and relatively slow during the middle of the day.

Table 10: Cross-listed securities: volatility dynamics

Table 10.A: Unconditional variance ratio

	Mean	Median	Min	Max
All	1.003	0.98	0.74	1.83
Quartile 1	0.96	0.94	0.86	1.17
Quartile 2	1.03	0.99	0.75	1.83
Quartile 3	1.01	1.002	0.74	1.45
Quartile 4	1.02	0.99	0.88	1.33
Spearman ro (US share, V. ratio)	0.25**			

Table 10.B: Conditional volatility dynamics

	NYSE/AMEX		TSE	
	Coef.	S.Error	Coef.	S.Error
ω	-0.258**	0.024	-0.252**	0.021
α	0.064**	0.008	0.058**	0.007
β	0.961**	0.003	0.961**	0.003
γ	-0.134**	0.018	-0.113**	0.014
δ	0.044**	0.006	0.052**	0.007
θ_{US}	-0.0053**	0.002	-0.0058**	0.002
θ_{CAN}	-0.0003	0.002	-0.0009	0.002
ρ	0.931**	0.0057		

Model: $\binom{\epsilon_{1,t+1}}{\epsilon_{2,t+1}} |\Omega_t \sim Dist\left(0, \sum_{t+1}\right)$

$$\sum_{t+1} = \begin{bmatrix} h_{1,t+1} & \rho(h_{1,t+1}h_{2,t+1})^{0.5} \\ \rho(h_{1,t+1}h_{2,t+1})^{0.5} & h_{2,t+1} \end{bmatrix}$$

$$\ln(h_{1,t+1}) = \omega_1 + \alpha_1 G_{1,t} + \beta_1 \ln(h_{1,t}) + \delta_1 G_{2,t} + \theta_{1,US} v_{US,t} + \theta_{1,CAN} v_{CAN,t}$$

$$\ln(h_{2,t+1}) = \omega_2 + \alpha_2 G_{2,t} + \beta_2 \ln(h_{2,t}) + \delta_2 G_{1,t} + \theta_{2,US} v_{US,t} + \theta_{2,CAN} v_{CAN,t}$$

$$G_{i,t} = \{|u_{i,t}| - E\,|u_{i,t}| + \gamma_i u_{i,t}\}, \quad u_{i,t} = \epsilon_{i,t}/h_{i,t}^{0.5}, \quad i = 1,2$$

** denotes significance at 5%

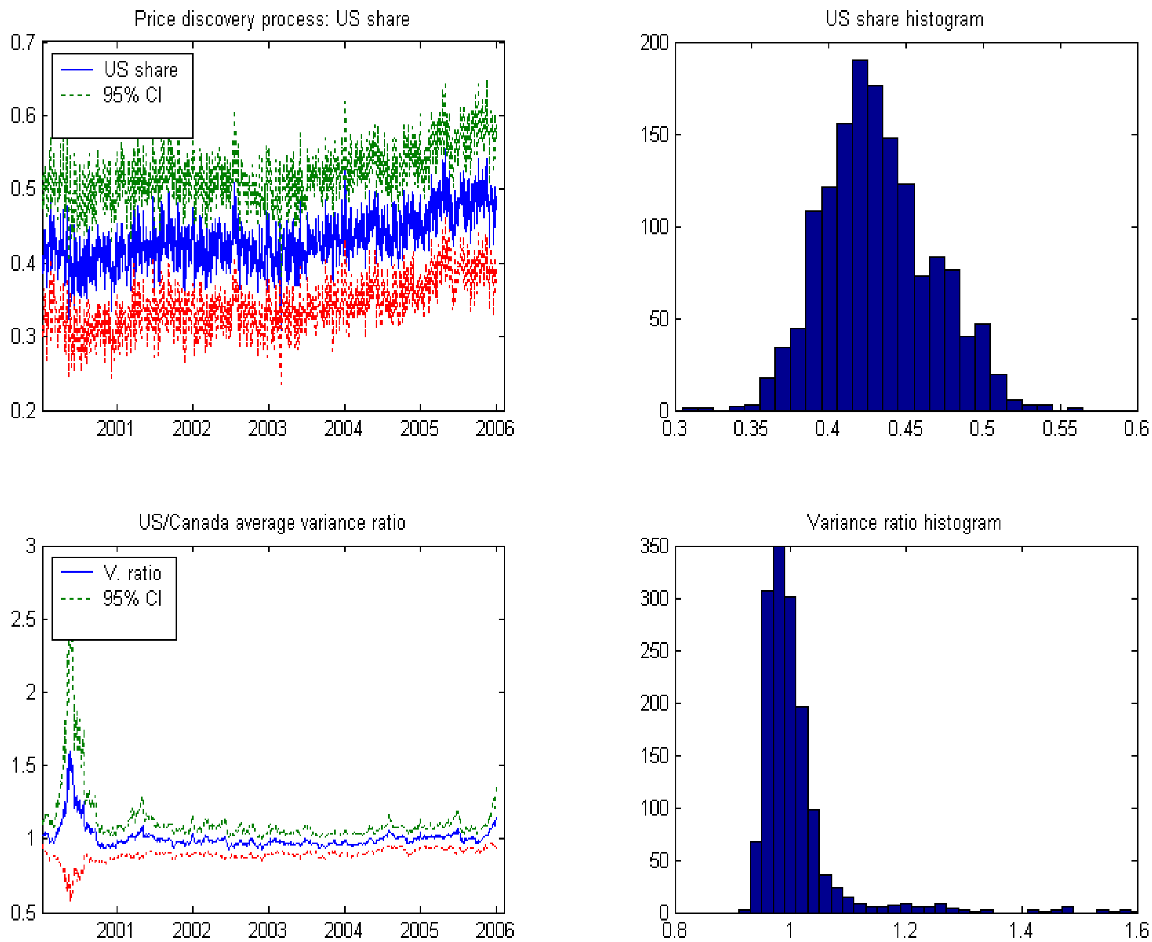

Figure 4-3: Price discovery and information flow dynamics

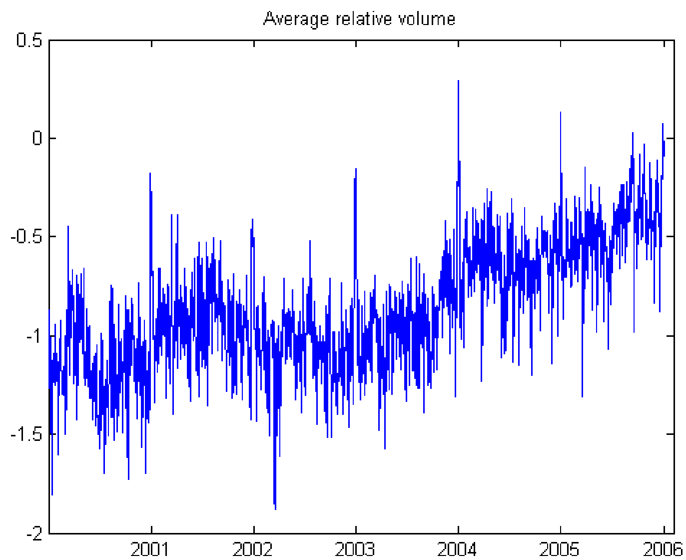

Figure 4-4: Average relative trading volume on the New-York and Toronto stock exchanges over the period of January 2000-December 2005

Chapter 5

The Sarbanes-Oxley Act of 2002: Implications for Market Efficiency and Analysts' Performance

5.1 Introduction

Transparent corporate disclosure of information is undoubtfully one of the corner stones needed for an efficient functioning of stock markets. Financial statements, reports, and announcements serve as a useful valuation tool both for analysts, who submit their forecasts and investment recommendations based on this data, and for the investors who use this information to price financial instruments and to choose optimal portfolio strategies. In this context the Sarbanes-Oxley Act (hereafter SOX act) is unanimously described as one of the most far-reaching and significant changes in the disclosure obligations of publicly traded companies (Smith, 2002, Ribstein, 2003). The purpose of this paper is to study the reaction of the stock market participants, the investors and the analysts, to this reform.

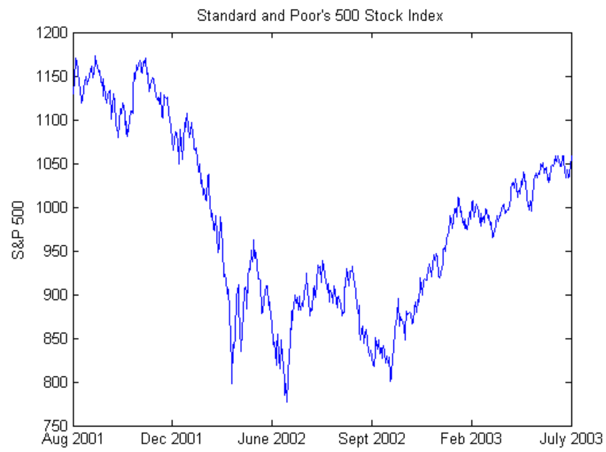

Figure 5-1: Standard and Poor's 500 composite over the period of 2001-2003

The Sarbanes-Oxley Act, signed into law on 30 July 2002, was enacted as a response to a series of severe corporate scandals that have shaken the confidence of the public in the stock markets in particular and in the financial institutions in general. On 16 October 2001 Enron Corporation announced a 35 million decrease in stated earnings and a 1.2$ billion loss of shareholder equity due to accountancy misreporting, a statement followed by the November announcement that an additional 500$ millions in earnings were overstated. On 2 December 2001 Enron declared itself bankrupt, making history as the largest bankruptcy in the corporate history of the United States. However, this was just the beginning. The bankruptcy of Global Crossing in January 2002 and Adelphia Communications in March 2002 due to inflated earnings, Xerox, admitting more than 6$ billion in overstated earnings on June 2002, and Worldcome, filing for bankruptcy on July 2002 - these are just a few landmarks that uncovered severe institutional and regulatory problems in the financial reporting of firms. The costs of these misreportings led scandals were severe: Standard and Poor's 500 index lost about 20 percent of its value during the year 2002 (see Figure 5.1). This decline has been accompanied by an upward shift in the Implied Volatility Index (VIX), indicating a sharp increase in overall market uncertainty (see Figure 5.2) and a downward shift in the consumer confidence index (Hevesi, 2003).

As a response to these multiple cases of corporate fraud the SOX act concerns the following key aspects (for the comprehensive reviews see Smith, 2002 and Ribstein, 2003 among others)

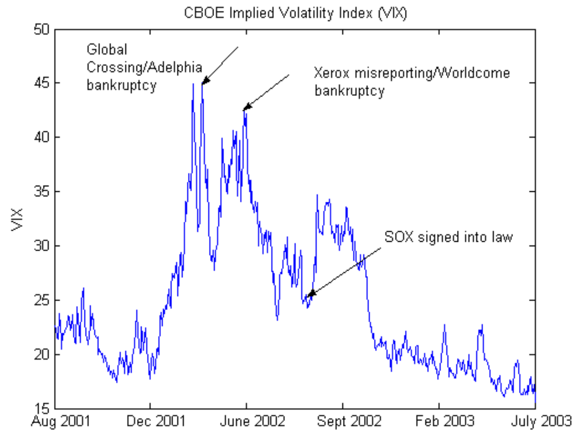

Figure 5-2: Implied Volatility Index (VIX) over the period of 2001-2003

1 New disclosure requirements. The companies are required to provide an internal control report as part of their annual report. Also, the quarterly and annual reports must disclose all off-balance sheet transactions and other material changes in their financial conditions on a "rapid and current basis". Insider trading reporting rules are substantially tightened as well.

2 Securities analysts regulation. A new regulation ensures the analysts' independence from their firms' investment banking activities.

3 Internal monitoring and gatekeeper regulation. More responsibility for the independent board audit committee for hiring and overseeing auditors; prohibits fraudulently influencing and/or misleading auditors; reducing ties between auditors and audited companies.

As the SOX act is aimed to increase the transparency of the information disclosure by the firms and, in this way, to restore the confidence of the public in the stock markets, an important question is whether this goal has been achieved. In particular, if the information disclosure did become more transparent and news is revealed on a more frequent and reliable basis, one would expect the stock prices to respond more rapidly to news regarding the financial and economic conditions of the companies. However, although the SOX act's primary goal was to increase the information disclosure, to the best of our knowledge, no study examines whether and, if so, to what extent the speed of adjustment to the new information of stock markets has changed after the Act has been signed into law. The first purpose of this paper is, therefore, to fill this gap by studying whether the informational efficiency of the US stock markets has changed following the SOX act.

Also, since corporate news is an important source of information for analysts, an increase in the information disclosure should increase the accuracy of the analysts' forecasts. However, if the Act has not succeeded in restoring public confidence, shaken by the corporate scandals, the picture might be reverse. In particular, we may expect both investors and analysts becoming more cautious in interpreting the news, which would result in stock prices reflecting more slowly the information on the one hand and the analysts' forecasts becoming overpessimistic on the other hand. The second purpose of this paper is, therefore, to study the implications of the SOX for the accuracy of the analysts forecasts.

In terms of methodology we estimate the partial adjustment model with noise of Amihud and Mendelson (1987), which we apply to all the stocks listed on NYSE/AMEX during the last decade. Within this framework we test for the presence of structural breaks in the speed of adjustment coefficients after the Act has been signed into law. Next, we apply nonparametric tests to the analysts forecasts and actual earnings data of the abovementioned firms to study whether the corporate scandals and the SOX act have influenced the performance of the analysts and, if so, in which direction.

We find strong support in favor of markets becoming more informationally efficient in the post SOX period, with average speed of adjustment exhibiting a substantial increase. On the other hand, we also find strong evidence of the analysts' forecasts becoming less accurate, and, in particular, more "overpessimistic" in the post SOX era. Though we also find some weak evidence in favor of the SOX act effecting the analysts' performance in the recent two years, overall the positive impact of the legislation appears to be overwhelmed by the impact of the corporate scandals which have distorted the confidence of the analysts in the information provided by the firms.

The remainder of this paper is organized as follows. In Section 5.2 we briefly overview some relevant literature on the stock market informational efficiency and the performance of the firms' analysts. Section 5.3 describes the data. In Section 5.4 we formulate our research questions and discuss the methodology applied in this paper. In Section 5.5 we present and discuss our estimation results. Finally, in Section 5.6 we present our concluding remarks and propose some directions for further research.

5.2 Literature Review

The concept of the "efficient market hypothesis" has been formalized by Fama (1970) and is related to the question of whether the pricing information is fully incorporated in stock prices. The question of market efficiency has been examined by an extant body of empirical studies. While providing a comprehensive review of the market efficiency literature is clearly out of the scope of this paper, we shall briefly review a number of widely cited studies in this field, related to the issue examined in this paper.[1] Amihud and Mendelson (1987) report significant violations from the null of a random walk in favor of ARMA(1,1) model for the sample of Dow Jones components, suggesting that stock prices do not fully adjust to a new information. Lo and Mackinlay (1988) reject the null that stock prices follow a random walk based on the variance-ratio test. Damodaran (1993) estimates the speed of adjustment coefficients for the NYSE/AMEX sample of stocks and finds that in general the stocks are characterized only by the partial adjustment to the partial adjustment or "underreact". In a more recent work Lo and MacKinlay (1999) find that short-run serial correlations are not zero and the existence of "too many" successive moves in the same direction suggests the existence of "momentum" in short-run stock prices, a finding supported by Theobald and Yallup (2004) who report an overall tendency of NYSE/AMEX listed stocks to underreact in the short run. Lo, Mamaysky, and Wang (2000) by using nonparametric techniques report that some technical analysis based rules do have some predictive power. Overall, these papers suggest that in a short-run the adjustment of stock prices to a new information is less than full, possibly due to investors' underreaction.

A number of studies examine the relationship between the market efficiency and information disclosure. Collins *et al.* (1987) and Freeman (1987) show that differences in information

[1] For a survey of the market efficiency literature a reader is refered to Schwert (2003)

environment affect the extent to which price changes anticipate earnings changes, a finding supported by Collins and Kothari (1989). Imhoff and Lobo (1992) find that earnings news have a greater impact on unexpected stock price change as the amount of pre-earnings-announcement uncertainty decreases. In a more recent study Douthett *et al.* (2003) find that earnings surprises tend to have a larger impact on the stocks of the firms which are required to report financial information under more stringent disclosure rules. Ng *et al.* (2006) provide evidence that the stocks of firms with higher quality disclosure are associated with a smaller underreaction. The overall conclusion of these studies is that the speed of adjustment of security prices to a new information is related to the quality of the information disclosure. In context of this study, an important question is whether the extent of underreaction has changed after the introduction of the SOX.

The second issue of interest is whether the enactment of the SOX act has influenced the performance of analysts, and, in particular, whether the analysts' forecasts of the companies' earnings became less biased[2]. Numerous studies indicate the presence of a bias in the analysts' earnings forecasts (see Brown (1993) for a review of the related literature). Fried and Givoly (1982) and O'Brien (1988) show that the analysts' earnings forecasts generally are overoptimistic. Similar results are reported by Stickel (1990) and Abarbanel (1991), who find that the mean estimate of the analysts' forecast errors is significantly negative. Lim (2001) proposes a model where analysts trade off bias to improve management access leading to optimal forecasts being overoptimistic. More recent studies, however, find that the sign of the bias is unstable over time. Brown (1997) documents significant rightward temporal shifts in mean earnings surprises between 1984 and 1996. Similar findings are reported by Brown (2001), which are consistent with firms' management desire to meet or beat analysts forecasts as reported by Degeorge *et al.* (1999).

Several studies examine the relationship between the forecast accuracy and the level of information disclosure. Waymire (1986) finds that the accuracy of the analysts earnings forecasts improves after the management earnings forecast is released. For the US firms Lang and Lundholm (1996) find that firms with more informative disclosure policies are followed by a larger

[2] A term "analysts' forecasts bias", as it is somewhat loosely used in academic literature, refers to a situation when the expected value of the analysts' forecast error (actual earnings minus concensus forecast) is different from zero.

number of the analysts and have more accurate analyst earnings forecasts. Basu, Hwang, and Jang (1998) find that country-average levels of disclosure are positively associated with analysts' levels of accuracy for the sample of seven countries. Similar results are reported by Khanna, Palepu, and Chang (2000) for a sample of 37 countries and by Hope (2002) for a sample of 22 countries. The overall conclusion from these and other studies is that higher disclosure enhances the analysts' forecast accuracy. Therefore, studying the question of whether the SOX act led to improvement in the analysts' performance is of major importance both for policy makers and for the practitioners who incorporate the analysts' earnings forecasts in their firm valuations.

5.3 Data Description

5.3.1 Sample Selection

Our database consists of daily observations on all NYSE/AMEX stocks with continuous data from January 1998 to December 2005. This data includes closing prices adjusted for splits, daily trading volume and the number of shares outstanding for each security included in our sample. The data has been obtained from the CRSP tapes. Similar data, though over a different time span, has been used in related studies by Damodaran (1993) and Theobald and Yallup (2004), though for different purpose. Following the standard convention we exclude from our analysis NASDAQ stocks. This screening rule leaves us with a total number of 1513 firms.

To study potential implications of the Sarbanes-Oxley act for the analysts's performance for all the firms included in our sample we collect data on their actual and predicted earnings over the period January 1998-June 2006 on a quarterly basis. More specifically, each firm-quarter observation includes actual earning, mean analysts' forecast, highest/lowest forecast estimates, and the announcement date. All data has been obtained from the Institutional Brokerage Estimate System (I/B/E/S). Following related studies (Datta and Dhillon,1993, Shane and Brous,2001) we define the consensus forecast as the mean forecast from the last month before the announcement date for each firm-quarter observation. To be included in our sample a firm must have at least two years (eight quarterly observations) both before and after July 2002 when the SOX has been signed into law. Also, to be included in our sample we require each observation to have at least two different analysts' estimates. To take care of possible outliers caused either by special items or by data input errors we filter our data with the Grubbs algorithm (Barnett and Lewis (1994)). After applying these filtering rules our final dataset consists of 24380 firm-quarter observations.

5.3.2 Exploratory Analysis

In this subsection we conduct an exploratory analysis of our data. First, we present the descriptive statistics and discuss the properties of stock returns of the firms included in our sample. Next, we conduct a preliminary analysis of the earnings and the analysts forecasts data.

Stock returns data

A number of studies report the speed of adjustment of the large capitalization stocks being different from those of the small size firms (Damodaran,1993; Theobald and Yallup, 2004). Therefore, for the purpose of further analysis we sort all the firms in our sample into ten deciles based on their average CRSP capitalization decile assignment during the time span of our study.

In Table 1.A we present some descriptive statistics of the daily close-to-close log returns ranked by their market capitalization as described above. For each statistic (mean, standard deviation etc) we report a cross-section average of the latter across all the securities according to their capitalization decile assignment. Most of the stocks exhibit positive drift which, starting from the fifth decile, becomes statistically significant. Also, for the stocks included in our sample the null hypothesis of normally distributed returns on average is strongly rejected based on a highly significant excess kurtosis. This excess kurtosis, however, can be partially attributed to GARCH-type effects, based on highly significant estimates of the autocorrelation coefficient between the squared returns. Raw returns on average also appear to be significantly autocorrelated, though both the sign and the magnitude of the estimates seem to change from significantly negative for the low decile portfolios to positive (though statistically insignificant) for the high-cap stocks. Interestingly, average estimates of both standard deviation and mean turnover almost monotonously increase from low to high-cap portfolios. Since both trading volume/turnover and volatility are usually considered to be a proxy for the information flow[3],

[3] See, for instance, Andersen (1996).

these findings suggest that trading in high-cap stocks is likely to be more informationally intensive. Finally, for all the stocks daily returns appear to be negatively skewed and the magnitude of skewness coefficient estimate tends to decline (though not monotonously) from the low to the high capitalization deciles. In conjunction with monotonously increasing turnover this finding can be attributed to Hong and Stein (2003) "dispersion of beliefs" model.

Table 1.A: Descriptive statistics-daily returns

Decile	1	2	3	4	5
Mean	0.0045	-0.0049	-0.0049	0.012	0.02**
St. Deviation	1.87	1.94	1.98	2.24	2.23
Skewness	-0.114*	-0.141**	-0.113**	-0.064**	-0.101**
Kurtosis	10.27**	10.08**	8.84**	8.79**	8.99**
Corr(r_t, r_{t-1})	-0.046**	-0.019**	-0.016**	0.004	-0.004
Corr(r_t^2, r_{t-1}^2)	0.163**	0.162**	0.164**	0.155**	0.148**
Daily Turnover	0.2	0.25	0.28	0.35	0.41

Decile	6	7	8	9	10
Mean	0.031**	0.024**	0.025**	0.028**	0.022**
St. Deviation	2.34	2.16	2.23	2.26	2.22
Skewness	-0.023	-0.064*	-0.033	-0.063**	-0.058**
Kurtosis	9.51**	9.11**	9.51**	8.95**	8.51**
Corr(r_t, r_{t-1})	-0.012**	-0.011**	-0.005	0.005	0.004
Corr(r_t^2, r_{t-1}^2)	0.147**	0.145**	0.146**	0.142**	0.16**
Daily Turnover	0.47	0.5	0.58	0.6	0.45

The estimates of the mean, standard deviation, and mean turnover are presented in percentage points. *(**) denoted significance at 10 (5)%. Corr(r_t, r_{t-1}) and Corr(r_t^2, r_{t-1}^2) denote serial correlation of raw and squared returns, respectively. Daily turnover is measured as the daily trading volume scaled by the total number of shares outstanding.

Earnings data

Next, we conduct a preliminary analysis of the "earning surprise" series which we define as actual earning minus consensus forecasts. For the purpose of further analysis we group all firms in our sample into five portfolios based on the extent to which actual earnings can be predicted by the analysts. Define by $\hat{\sigma}^2_{e,i}$ the estimated variance of the actual earnings for a company i. Also, denote by $\hat{\sigma}^2_{\epsilon,i}$ the estimated variance of the forecast errors for that company. We group all the firms included in our sample into five portfolios based on the variance-ratio criterion, that is, based on the value of their $\frac{\hat{\sigma}^2_{\epsilon,i}}{\hat{\sigma}^2_{e,i}}$ ratio. This measure, calculated for each firm, provides us the information on how well the analysts' forecasts explain the variation of the actual earnings. The first portfolio includes the stocks with the lowest (first quintile) variance ratio while the fifth portfolio includes the firms with the highest (fifth quintile) variance ratio estimates.

Descriptive statistics are reported in Table 1.B. A number of interesting observations can be mentioned. First, the earning surprise series appears to be highly leptocurtic with estimates of kurtosis significantly exceeding the one corresponding to the normal distribution. Also, the earning surprises on average exhibit higher dispersion as we move from the lower to the upper quintiles, based both on the estimates of the standard deviation and average spread (highest forecast minus lowest forecast). The estimates of mean and skewness are particularly interesting. First, we find the mean of the earning surprise to be significantly negative for all the portfolios included in our sample, a finding which suggests that on average analysts tend to submit overpessimistic forecasts. This finding is consistent with the results of Degeorge *et al.* (1999) and Burgstahler and Eams (1998) who report that companies' management tends to report earnings that meet or beat analysts forecasts. Interestingly, both mean and skewness estimates tend to decline from lower to upper quintile portfolios, with skewness switching from positive and significant to slightly negative, suggesting that the degree of the analysts overpessimism tends to decline with an increase in ex-post uncertainty. These findings can be attributed to the bias-variance trade-off as suggested by Lim (2001). To test this conjecture in a last row of Table 1.B we report sample correlations between the earning surprise and spread, which can be interpreted as an *ex ante* measure of the uncertainty, that is, a measure of the analysts' dispersion of beliefs. While being statistically insignificant for the portfolios 3-5, for the lower quintile portfolios the estimates are positive and statistically significant, suggesting that during periods of high uncertainty analysts are likely to become more dependent on the information they receive from the company management.

Table 1.B: Descriptive statistics-earning surprises

Quintile	1	2	3	4	5
Mean	0.015**	0.016**	0.012**	0.011**	0.007**
St. Deviation	0.034	0.056	0.065	0.077	0.101
Skewness	0.841**	0.459**	0.093	-0.146	-0.17
Kurtosis	7.82**	7.71**	8.16**	7.78**	8.1**
Mean spread	0.057	0.086	0.088	0.097	0.084
Corr(spr,surp)	0.17**	0.11**	-0.001	0.004	0.018

earnings surprise is measured as the actual earning - mean forecast

forecast spread is measured as the highest - lowest analysts' forecast

Corr(spr,surp) denotes sample correlation between the earnings surprise and forecast spread. ** denotes significance at 5%

5.4 Research Questions and Methodology

5.4.1 Market Efficiency

Following a definition proposed by Schreiber and Schwartz (1986), a price discovery process is a process during which the stock price converges to its equilibrium or "intrinsic" value. When the markets are fully efficient any change in intrinsic value of the firm should be immediately reflected in its stock price. Following this concept, the question of whether the market has become more (less) informationally efficient due to some market-wide event can be analyzed by comparing the speed of adjustment coefficients before and after the event has occurred.

As noted by Fama (1992), testing the hypothesis of stock markets being informationally efficient is in fact a test of a joint hypothesis of market efficiency and correct specification of the model. Following Damodaran (1993), Theobald and Yallup (2004) and other related papers, our study of the market efficiency is based on a partial adjustment with noise model of Amihud and Mendelson (1987) (denoted as A&M model). This model explicitly specifies stochastic processes for the observed log-price series and the underlying latent intrinsic value series. The log of the intrinsic value is assumed to follow a random walk with drift, thus, assuming that the equilibrium *unobserved* price is fully efficient in a sense that it immediately incorporates any information shock. The *observed* price and the intrinsic value of firm i at period t are specified as

$$\Delta P_{i,t} = \pi_{i,t}(V_{i,t} - P_{i,t-1}) + u_{i,t} \qquad i = 1, ...n,\ t = 1, ...T$$

$$\Delta V_{i,t} = \mu_i + e_{i,t}$$

where $\Delta P_{i,t} = P_{i,t} - P_{i,t-1}$ denotes the change in the observed price, $V_{i,t}$ is the unobserved intrinsic value (both expressed in natural logarithms), $\pi_{i,t}$ is the speed of adjustment coefficient which lies in interval $(0, 2)$ to keep the observed return process stationary, μ_i and $e_{i,t}$ are the drift term and the information shock to the intrinsic value, respectively, and $u_{i,t}$ is a bid-ask spread related noise. Both $u_{i,t}$ and $e_{i,t}$ are assumed to have zero mean and to be serially and cross sectionally-uncorrelated at all leads and lags. In this setting, a fully efficient market corresponds to the case of $\pi_{i,t}$ being equal to 1 for all the firms. When $\pi_{i,t}$ lies between 0 and 1 investors systematically underreact to the news, while for $\pi_{i,t}$ lying in interval $(1, 2)$ overreaction occurs.[4]

Theobald and Yallup (2004) show that the observed price process can be easily reformulated as

$$\Delta P_{i,t} = \pi_{i,t}\mu_i + (1 - \pi_{i,t})\Delta P_{i,t-1} + \pi_{i,t}e_{i,t} + u_{i,t} - u_{i,t-1}$$

A General Method of Moments (GMM) estimator of $\pi_{i,t}$ based on instrument variables can be easily constructed and estimated (the choice of the instruments will be discussed in the following section).[5].

The A&M model provides a simple and intuitive way of analyzing the process of markets incorporating new information with the speed of adjustment π being the key parameter of interest. Within this framework we are interested in studying the following research questions

[4] In the original model of Amihud and Mendelson (1987) $\pi_{i,t}$ is assumed to be constant for each firms. In this paper we allow it to be time varying which is important for our hypothesis development.

[5] Alternatively, one can simply estimate 2) as ARMA(1,1) model, as proposed by Theobald and Yallup. Also see Damodaran (1993)

Q1: Was the speed of adjustment stable over the last decade? If not, when did this change occur?

In the original A&M model the speed of adjustment π is assumed to be time-invariant, that is, $\pi_{i,t} = \pi_i$. We examine this issue by testing the following null hypothesis for each firm included in our sample

$$H_0 : \pi_{i,t} = \pi_i \ \forall \ t = \{1, 2......T\}$$

against the alternative that there has been a structural shift at some t^* lying between 1 and T, the time span of our study. That is, under the alternative for each firm the speed of adjustment is piecewise constant and equals to $\pi_{i,S1}$ before the structural break has occurred and $\pi_{i,S2}$ in the post-break period, with the indices b and a denoting before and after the structural shift, respectively. We apply two different tests: the supremum Wald test of Andrews (1993) and the exponential Wald test developed by Andrews and Ploberger (1994). While, as shown by Andrews and Ploberger (1994), the latter test enjoys certain optimality properties (which is not the case for the former), the supremum Wald test also allows us to determine *when* a structural break has occurred, given that the null of parameter stability has been rejected.

Consider the sample of length T, which is partitioned into two subsamples with sample lengths $\alpha T \in \mathbb{N}$ and $(1-\alpha)T \in \mathbb{N}$ respectively for some α lying in a given interval $[\alpha_l, \alpha_u]$ with α_l and α_u denoting the lower and the upper bound of the interval respectively. Also, define by $\hat{\pi}_{\alpha T}$ and $\hat{\pi}_{(1-\alpha)T}$ the GMM consistent estimators of π_{S1} and π_{S2}, respectively, based on the first and second subsample and by $\hat{V}_{\alpha T}$and $\hat{V}_{(1-\alpha)T}$the estimates of the variance of $\hat{\pi}_{\alpha T}$ and $\hat{\pi}_{(1-\alpha)T}$, respectively. Then the standard Wald statistic which tests the null $\pi_{S1} = \pi_{S2}$takes the following form (see Andrews (1993))

$$W_T(\alpha) = T(\hat{\pi}_{(\alpha T)} - \hat{\pi}_{((1-\alpha)T)}) \left\{\alpha^{-1}\hat{V}_{(\alpha T)} + (1-\alpha)^{-1}\hat{V}_{((1-\alpha)T)}\right\}^{-1} (\hat{\pi}_{(\alpha T)} - \hat{\pi}_{((1-\alpha)T)})$$

and has asymptotic χ^2_1 distribution under the null. The supremum Wald statistics is calculated as follows

$$\begin{aligned} SW_T &= \sup_{\alpha} W_T(\alpha) \\ s.t. \alpha &\in \{\alpha_l, \alpha_u\} \end{aligned}$$

and the exponential Wald statistic equals to

$$\exp(W_T) = \ln\left\{\frac{1}{\alpha_u T - \alpha_l T + 1}\sum_{i=0}^{K}\exp(\frac{1}{2}W_T(\alpha_l + (\alpha_u - \alpha_l)\frac{i}{K}))\right\}$$

The limiting distributions of these two statistics under the null were derived by Andrews (1993) and Andrews and Ploberger (1994), respectively, who also provide the tables of the corresponding critical values for different levels of significance. More specifically, this procedure involves estimation of a series of usual Wald statistics over a finite grid of K partitioning points of the whole time span of the study. Following Andrews we choose the interval of α equal to $[0.15, 0.85]$ with a grid of 22 trading days (approximately one trading month). This procedure leaves us with 65 potential change points per stock during the time span of our study.

We are interested not only in *whether* but also *how* the speed of adjustment changed after the introduction of the SOX and whether this change (if it occurred) has led to an increase in the informational efficiency of stock market. This leads to the following two research questions.

Q2: Has the average speed of adjustment for the firms included in our sample increased or decreased following the enactment of SOX reform?

To answer this question the following null hypothesis is tested

$$H_0 : N^{-1}\sum_{i=1}^{N}\pi_{i,S1} = N^{-1}\sum_{i=1}^{N}\pi_{i,S2}$$

with $\pi_{i,S1}$ ($\pi_{i,S2}$) denoting the speed of adjustment of firm i before (after) the SOX act has been signed into law and N is the number of firms in the population. For each cap decile we conduct a pairwise t-test where the population averages are replaced by their sample analogues $n^{-1}\sum_{i=1}^{n}\hat{\pi}_{i,S1}$and $n^{-1}\sum_{i=1}^{n}\hat{\pi}_{i,S2}$ with n denoting the number of firms included in each decile. A significant increase of the cross-sectional average of the speed of adjustment estimates in the post SOX period will indicate that following the reform US markets incorporate more rapidly new information.[6]

[6] In this study we focus on the mean spead of adjustment as the measure of location of the distribution of the speed of adjustment coefficients. While it is out of scope of this paper, one could also test for the breakpoints in the higher moments of the speed of adjusment distribution, e.g. variance, skewness etc, though the results of these tests would be harder to interpret.

Q3: Have the US markets become more efficient following the enactment of the SOX reform?

Since in the A&M model full market efficiency is defined as a case when the speed of adjustment π is equal to unity for each stock traded on the market, a natural way of testing for change in market efficiency is by measuring the average distance between the vector of the speed of adjustment parameters and the unity vector. In this study we base our analysis on two different distance measures, the average L_1 distance (here *Abs.Dist*) and average squared L_2 distance (here *Sq.Dist*) which we define as $N^{-1}\sum_{i=1}^{N}|\pi_i - 1|$and $N^{-1}\sum_{i=1}^{N}(\pi_i - 1)^2$, respectively, for each cap-portfolio. We test for a change in market efficiency by testing the following null hypotheses via a pairwise t-test

$$Abs.Dist_{S1} = Abs.Dist_{S2}$$

$$Sq.Dist_{S1} = Sq.Dist_{S2}$$

where again absolute and squared distance measures are replaced by their sample analogues $n^{-1}\sum_{i=1}^{n}\left|\overset{\wedge}{\pi}_{i,b} - 1\right|$ and $n^{-1}\sum_{i=1}^{n}\left(\overset{\wedge}{\pi}_{i,b} - 1\right)^2$ for pre-SOX period and $n^{-1}\sum_{i=1}^{n}\left|\overset{\wedge}{\pi}_{i,a} - 1\right|$and $n^{-1}\sum_{i=1}^{n}\left(\overset{\wedge}{\pi}_{i,a} - 1\right)^2$, respectively. An increase in market efficiency should result in a significant decline in the distance measures following the reform.

5.4.2 Analysts' Performance

A second issue we consider in this paper is the impact of corporate scandals and the SOX reform on the accuracy of the analysts forecasts, in particular, on their bias. The analysis is performed separately for each one of the five variance ratio ranked portfolios, formed as described in subsection 5.3.2. To set forth notations, we denote by n^* the sample size for each portfolio which is equal to the total number of firms included in each portfolio, that is, n from the previous subsection multiplied by the average number of observation over the time dimension per company. We examine the following research questions

Q4: Were the analysts' consensus forecasts the "best" earnings forecasts both before and after the enactment of the reform?

Denote the actual quarterly earning by $e_{i,t}$ and the consensus forecast by $c_{i,t}$, where $i =$

$1, ...n$ denotes the index of the company and t denotes the forecast period. We test whether the analysts' consensus forecasts were the "best' earnings forecasts both in the pre-and post SOX periods, which corresponds to testing the following null hypothesis

$$H_0 : E(e_{i,t} \,|c_{i,t} = c) = c \;\forall c \in C$$

where $E(e_{i,t} \,|c_{i,t} = c)$ denotes expected actual earning conditional on a latest consensus forecast c and C denotes the support of $c_{i,t}$. In particular, under the null, analysts' consensus forecasts are neither "overpessimistic" nor "overoptimistic". We test this hypothesis by using two alternative tests. The first one is the test proposed by Gozalo (1993). In our context, he suggests to use the following statistic

$$T = (n^* h)^{1/2} \hat{v}_c^{-1/2} \left(\hat{E}(e_{i,t} \,|c_{i,t} = c) - c \right)$$

Here c is the value of a randomly selected consensus forecast and $\hat{E}(e_{i,t} \,|c_{i,t} = c)$ is a nonparametric Nadaraya-Watson estimate of the expected earning conditional on that value of the consensus forecast. Also, $v_c = \hat{f}(c) \hat{\sigma}_\epsilon^2 \int K(\psi)^2 d\psi$ with $\hat{f}(\cdot)$ being a nonparametric estimate of a density function of $c_{i,t}$ evaluated at the point c, $K(\cdot)$ is a kernel and $\hat{\sigma}_\epsilon^2$is the estimate of the variance of the forecast error $\epsilon_{i,t} = e_{i,t} - E(e_{i,t} \,|c_{i,t} = c)$. The choice of the bandwidth h is based on a cross-validation criterion. Under the null of a correct parametric specification the limit distribution of the test statistic is standard normal. Gozalo (1993) proposes to look at the supremum of T evaluated at d randomly chosen points. Since this test is potentially oversized, instead, we calculate the statistic $T_{(G)} = \sum_{j=1}^{d} T_j^2$ which is asymptotically $\chi^2(d)$ distributed under the null (see Pagan and Ullah, 1994 for a comprehensive discussion of estimation and testing in a nonparametric framework).

A second test has been proposed by Stute (1997). He proposes considering the empirical process $R_n(c_0) = n^{-1/2} \sum_{t=1}^{T} \sum_{i=1}^{n} \epsilon_{i,t} I(c_{i,t} \leq c_0)$ where $\epsilon_{i,t} = e_{i,t} - c_{i,t}$, that is, the earning surprise under the null of the consensus forecast being the "best" forecast, and using a functional of this process as test statistic. Following Miles and Mora (2003) we consider the Cramer-von Mises statistic

$$T_{(S)} = n^{*-2} \sum_{t^*=1}^{T} \sum_{j=1}^{n} \left[\sum_{t=1}^{T} \sum_{i=1}^{n} \epsilon_{i,t} I(c_{i,t} \leq c_{j,t^*}) \right]^2$$

whose asymptotic distribution can be approximated by the "wild bootstrap" procedure (Stute,1997).[7]

Our interest is not only in whether the analysts' forecasts were the optimal forecasts before and (or) after the reform, but also whether the former became more or less accurate, following the introduction of the SOX act. Therefore, we examine the following question.

Q5: Has there been a structural shift in the conditional dynamics of the analysts' forecasts errors following the introduction of SOX, and if so, in which direction?

Testing the intertemporal stability of the conditional dynamics of the analysts' forecasts errors corresponds to testing the following null hypothesis

$$E_{S1}(\epsilon_{i,t} \,|x_{i,t} = x) = E_{S2}(\epsilon_{i,t} \,|x_{i,t} = x) \;\; \forall x \in X$$

where $\epsilon_{i,t}$ is the forecast error defined as $e_{i,t} - c_{i,t}$, $x_{i,t}$ is a conditioning variable with support X and $E_{S1}(\epsilon_{i,t} \,|x_{i,t} = x)$ and $E_{S2}(\epsilon_{i,t} \,|x_{i,t} = x)$ are the conditional expectations of the analysts' forecast error given $x_{i,t}$ in pre-and post-SOX periods respectively. The choice of the conditioning variables will be discussed in the following section. To test this hypothesis we use the following Gozalo-type statistic

$$T_{break} = (n^*h)^{1/2} \left(\alpha_{S1}^{-1} \hat{v}_{S1,x} + (1-\alpha_{S1})^{-1} \hat{v}_{S2,x} \right)^{-1/2} \left(\hat{E}_{S1}(\epsilon_{i,t} \,|x_{i,t} = x) - \hat{E}_{S2}(\epsilon_{i,t} \,|x_{i,t} = x) \right)$$

Here $\hat{E}_{S1}(\epsilon_{i,t} \,|x_{i,t} = x)$ and $\hat{E}_{S2}(\epsilon_{i,t} \,|x_{i,t} = x)$ are the nonparametric estimates of the expected forecast error for a given value of the conditioning variable $x_{i,t}$ before and after the SOX has been signed into law, α_{S1} partitions our sample into pre-and-post SOX subsamples similar to Andrews (1993) test and $\hat{v}_{S1,i,t}(\hat{v}_{S2,i,t})$ are the estimates of its variance v before (after) the SOX act with the same formula as in standard Gozalo test. As in case of the standard Gozalo test we base our inference on the statistic evaluated over d randomly selected points, $T_{(G),break} = \sum_{j=1}^{d} T_{break,j}^2$, which is asymptotically $\chi^2(d)$ distributed under the null. The underlying intuition behind

[7] Miles and Mora (2003) also provide a brief description of this procedure.

this statistic is that $\hat{E}_{S1}(\epsilon_{i,t}\,|x_{i,t}\,)$ and $\hat{E}_{S2}(\epsilon_{i,t}\,|x_{i,t}\,)$ should asymptotically converge to the true conditional expectation which should be the same under the null that no structural shift has occurred . Finally, to test the direction of the structural shift, that is, whether the conditional bias has increased or declined, we test the equality of Spearman rho's in both periods

$$H_0 : \rho_{S1}(\epsilon_{i,t}, x_{i,t}) = \rho_{S2}(\epsilon_{i,t}, x_{i,t})$$

via standard pairwise $t-$tests.

5.5 Empirical Results

In this section we present and discuss our empirical results. First, we study the implications of the SOX for the informational efficiency of the US stock markets within the A&M model framework, as described in a previous section. The results are presented in the subsection 5.5.1. Next, we turn to the evaluation of the reform's impact on the analysts' performance. We present and discuss our findings in subsection 5.5.2.

5.5.1 SOX and Market Efficiency

Q 1. Was the speed of adjustment stable over the last decade? If not, when has a structural break occurred?

We start with the estimation results of the A&M model. More specifically, we test for a structural shift of the speed of adjustment coefficient π after the reform has been signed on 30 July 2002. While testing for a structural break when the date of a break is assumed to be known is a straightforward procedure, we find it more sensible to start our analysis with testing for parameter stability without determining a change point *a priori*. The reason for applying this approach is that if the structural shift is detected, it still can be potentially attributed to some other event, such as the collapse of the internet "bubble" or the September 11 events, both of which happened during the time span used in our study. Thus, by allowing the structural breakpoint to be endogenously determined we do not only test for a structural shift but also determine the event which has potentially triggered the latter. To test the stability of the speed of adjustment we apply Andrews supremum Wald (1993) and Andrews and Ploberger (1994) exponential Wald tests as described in a previous section.

Testing results are presented in Table 2. Since it is unrealistic to present the results for each security separately, instead, we present the rejection rates which we define here as a number of securities for which the null of the speed of adjustment stability has been rejected divided by the total number of stocks. Since we partition our sample on monthly basis by using 22 days grid and not on a daily basis (which would be a highly computationally intensive procedure), the test is likely to be conservative. Therefore, for both supremum Wald and the exponential Wald tests we take the significance level of 10 percent The rejection rates are calculated for each cap-based portfolio.

Table 2: Results of the sup(W) and exp(W) tests

Decile	1	2	3	4	5
SW rejection rate	0.19**	0.14	0.29**	0.39**	0.42**
ExpW rejection rate	0.16*	0.17**	0.32**	0.45**	0.47**
Decile	6	7	8	9	10
SW rejection rate	0.52**	0.46**	0.49**	0.35**	0.37**
ExpW rejection rate	0.52**	0.48**	0.49**	0.36**	0.35**

Notes: Rejection rate is defined as the number of firms for which a sup Wald statistic is significant at 10% level divided by a total number of firms included in each decile. Critical values for sup(W) and exp(W) tests can be found in Andrews (2003) and Andrews and Ploberger (1994). *(**) denotes that the rejection rate is significantly different than 0.1 at 10(5)% significance level

The results of the supremum Wald test indicate that for the low-cap stocks, in particular those assigned to the first and second deciles, the null of a stable speed of adjustment is rejected only for a small number of firms. For the second decile the rejection rate statistically does not exceed ten percent, that is, the significance level of the test. On the other hand, the results are strikingly different as we move to higher deciles. Starting from decile 4 we find both statistically and economically significant evidence of a structural shift in the information adjustment mechanism. Rejection rates for deciles six, seven, and eight are especially striking, where a structural break in the speed of adjustment is detected for approximately every second security. The overall conclusion might be that, if the structural break is due to the reform, its impact is substantially more pronounced for the high-cap stocks. This finding can be related to the fact that high-cap stocks, being well known by (or "visible" to) the investors, are more intensively traded than the stocks of the firms with low market value, and, therefore, we would expect the former to respond more rapidly to the reform than the latter. These findings are corroborated by the results of the exponential Wald test where the evidence of a structural shift in a speed of adjustment mechanism is even more pronounced, possibly due to the optimality properties of this test. Overall, based on both tests, we find substantial evidence of the intertemporal instability of the speed of adjustment coefficients.

An interesting question is not only *whether*, but also *when* a structural shift has occurred, i.e., whether the structural shift in the speed of adjustment is indeed related to the Sarbanes-Oxley reform and not to some other event. To shed some light on this issue, we plot in Figure 5.3 the relative frequency of rejections over the time span used in our study. More specifically, for each trading month between March 1999 (which corresponds approximately to $\alpha = 0.15$) and October 2004 (which corresponds to $\alpha = 0.85$), we define the relative share of rejections which occurred during that particular month out of the total number of rejections. The results clearly show a substantial cluster of the structural breaks occurring in 2002, the year of the reform, with two spikes around June-July 2002 and August-September 2002. Interestingly, we also find a cluster (though of less substantial magnitude) of the structural breaks around March 1999-April 2000, a finding that can be related to the collapse of the "dot.com" bubble. Also, we find a single spike of structural breaks the week following September 11, 2001. Overall, the findings of the Andrews (1993) stability test clearly indicate both instability of the speed of adjustment mechanism and the reform of 2002 being a potential source of the former.

Q2 and Q3. Has the average speed of adjustment for the firms included in our sample increased or decreased following the enactment of SOX reform? Have the US markets become more efficient following the enactment of the SOX reform?

We now turn to the evaluation of the impact, the reform of 2002 had on the speed of

Figure 5-3: Relative frequency of the structural shifts in the speed of adjustment coefficents for the NYSE/AMEX stocks

adjustment of the US stock market to a new information. Based on the findings of Andrew's (1993) stability test, the most substantial cluster of structural shifts has occurred in 2002. Therefore, in the following analysis we split our sample into two subsamples: January 1998-December 2001 and January 2002-December 2005 which we denote as S1 and S2 respectively. For each security included in our sample, we estimate the speed of adjustment coefficient π during the first and second sub-period and report its cross-sectional average for each of ten cap-sorted portfolios. We apply the GMM theory of Hansen (1982) where as instruments we choose Fama-French factors. The following set of moments is used to estimate the speed of adjustment for each security

$$E\left\{\begin{array}{l} MKT_{t-1} \\ SMB_{t-1} \\ HML_{t-1} \end{array} (\Delta P_{i,t} - \pi_i \mu_i + (1-\pi_i)\Delta P_{i,t-1})\right\} = 0$$

where MKT_t denotes the return on market portfolio, SMB_t denotes the return on a portfolio of small size stocks minus high capitalization stocks portfolio, and HML_t denotes the return on "value" stocks portfolio;io minus "growth" stocks portfolio. Daily data on these factors has been obtained from CRSP. Our preliminary analysis suggests that for our sample these factors on average capture above 20 percent of the total variation of stock returns while on the other hand we would expect these factors to be uncorrelated with bid-ask spread related noise of the individual stock, properties that make these factors suitable instruments.

The results are presented in Table 3. A number of interesting findings can be noted. First, consistent with findings of Theobald and Yallup (2004) we find that on a daily basis investors tend to underreact to the news with most of the average estimates of π being significantly lower than unity. Also, we find that on average the extent to which investors underreact tends to decline from low to high-cap portfolios, suggesting that high-cap stocks tend to reflect more rapidly new information, compared to the ones with low market capitalization. This finding is consistent with a "lead-lag" effect (e.g. Chordia and Swaminathan, 2001). Also, for the low-cap portfolios the estimates of the speed of adjustment tend to exhibit a higher cross-sectional dispersion.

Next, we turn to the main issue, namely, the impact of the Sarbanes-Oxley reform on the speed of adjustment and market efficiency. Starting with low cap portfolios, in particular, the first decile, we find that, though on average the speed of adjustment to the information shocks has increased, it lacks statistical significance. The picture is similar for the distance measures, both of which have declined after the reform, but the difference between the distance measures in the pre- and post-SOX periods lacks statistical significance.. However, starting from decile 2 the results change dramatically. Starting with the analysis of the adjustment coefficients, we find a dramatic increase in the former, an increase which is both economically and statistically significant. An increase in the speed of adjustment coefficients is becoming more pronounced as we move from the low to high cap stocks. Our results indicate that, following the reform on July 2002, the speed of adjustment to the information shocks increased on average by more than 15%, suggesting that after the reform, the US stock market responds more rapidly to the new information. The analysis of the two distance measures supports these findings. Similarly to the speed of adjustment estimates, starting from cap-decile 2, we find both an economically and statistically significant decrease in both the absolute and squared distance measures. Our findings suggest that on average the Sarbanes-Oxley reform resulted in a decrease of more than

36% of the mean absolute distance, while a mean squared distance declined almost twice![8] Overall, these findings suggest that based on the A&M model of partial adjustment, the reform of 2002 indeed led to an increase in market efficiency.

Table 3: Speed of adjustment estimates-A&M model

Decile	1		2		3		4		5	
Sample	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2
Speed of Adj.	0.518^{**}	0.589^{**}	0.449^{**}	0.474^{**}	0.648^{**}	0.755^{**}	0.706^{**}	0.853^{**}	0.776^{**}	0.939^{**}
p-value	0.4		0.09		0.01		0.00		0.00	
Abs.Dist	0.519	0.476	0.595	0.527	0.426	0.286	0.331	0.23	0.245	0.168
p-value	0.57		0.00		0.00		0.00		0.00	
Sq.Dist	0.619	0.328	0.429	0.297	0.285	0.179	0.151	0.107	0.092	0.055
p-value	0.36		0.00		0.09		0.02		0.03	
Decile	6		7		8		9		10	
Sample	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2
Speed of Adj.	0.858^{**}	0.977	0.879^{**}	0.963^{**}	0.845^{**}	0.959^{**}	0.856^{**}	0.975	0.916^{**}	1.019^{**}
p-value	0.00		0.00		0.00		0.00		0.00	
Abs.Dist	0.205	0.137	0.178	0.117	0.174	0.095	0.154	0.083	0.128	0.083
p-value	0.00		0.00		0.00		0.00		0.00	
Sq.Dist	0.068	0.041	0.05	0.027	0.044	0.015	0.036	0.013	0.025	0.013
p-value	0.02		0.00		0.00		0.00		0.00	

Notes: Speed of Adj. denotes sample mean estimate of π, Sq.Dist and Abs.Dist denote average squared and average absolute distance of π from the unity vector. We test the null: Speed of Adj.$_{(S1)}$ =Speed of Adj.$_{(S2)}$ Abs.Dist.$_{(S1)}$ =Abs.Dist.$_{(S2)}$ and Sq.Dist.$_{(S1)}$ =Sq.Dist.$_{(S2)}$. Corresponding p-values are reported in the row below.

We conduct a number of robustness checks. The results of Andrews (1993) stability test

[8] Since in our study the time dimension T is substantially larger than the dimension of the cross-section N we assume that T is of the higher order than N. Under this assumption the estimation inaccuracy of the $\hat{\pi}$-s is asymptotically irrelevant.

suggest that a substantial number of structural breaks can be potentially attributed to the collapse of the "dot.com" bubble and not to the SOX reform. Therefore, as a first robustness test we reestimate the speed of adjustment coefficients for the first subsample from which we exclude the period between March 1999 and March 2000. Overall, the results remain unaltered with cap-decile 7 being the only exception where an increase in the speed of adjustment turned out to be statistically insignificant. Next, we test whether our results could be due to the fact that we used only the stocks with continuous data over the whole sample period. If investors learn over time, one would expect to observe a gradual increase in the spead of adjustment, which could be mistakenly attributed to the impact of the reform. While indeed for a number of portfolios the speed of adjustment coefficients exhibit a significant time trend, the latter is significantly negative, a finding that suggests that our results are not driven by a selection bias problem. The investors' hypothetical learning curve also fails to explain a large cluster of structural breaks around the reform date. Finally, we reestimate the speed of adjustment coefficients for the second subsample from which we excluded the period between January and December 2002, the "breakpoint year" when the reform has been signed. An increase in the speed of adjustment coefficients becomes even more pronounced and also becomes statistically significant for the second decile. An overall impression is that our findings are fairly robust.

5.5.2 SOX and the Analysts' Performance

Next, we turn to the analysis of the analysts's performance in the pre- and-post Sarbanes-Oxley periods. All firms are grouped into five portfolios based on a variance ratio criterion, as described in subsection 5.3.2. The bias-variance trade-off models of Das *et al.* (1998) and Lim (2001) suggest that the analysts issue intentionally biased forecasts in order to improve access to managers' private information. Consequently, an improved access to managers' private information would result in a lower variance ratio. Also, based on the underlying logic of the bias-variance trade-off models, the analysts' forecasts of the companies with low variance ratio are more likely to be biased, i.e. overoptimistic if the managers prefer overoptimistic forecasts, or overpessimistic if the firms' management follows "meat or beat" analysts' forecast tendency. Therefore, if the analysts covering the low variance ratio companies are more dependent on access to managers' private information, we would expect the accuracy of their forecasts to be more affected by the new disclosure rules on the one hand, and the corporate scandals on the other hand. In other words, if the structural shift in the analysts' forecasts accuracy is detected in the post-SOX act period, we would expect it to be more pronounced for the low variance-ratio firms.

Q.4. Were the analysts' consensus forecasts the "best" earnings forecasts both before and after the enactment of the reform?

We begin with the analysis of the expected forecast error, conditional on the consensus forecast, which we define as the difference between the conditional expected earning given the consensus forecast for a particular quarter and the consensus forecast. Consider the following decomposition of the "best" earnings forecast

$$E(e_{i,t} \,|c_{i,t} = c\ ) = c + \Big(E(e_{i,t} \,|c_{i,t} = c\ ) - c\Big)$$

The last term at the right hand side of the equation can be considered as the correction factor, one can use to improve the performance of the consensus forecast For each sub-period we test the null hypothesis that the correction factor is equal to zero or, in other words, that the consensus forecast is the "best" forecast. As discussed in the previous section, we base our analysis on both non-parametric (Gozalo, 1993) and conditional moments type (Stute, 1997) tests. Since nonparametric tests typically are substantially sensitive to the choice of bandwidth, using the "nonsmoothing" type of tests such as the one proposed by Stute (1997) is a useful check of the robustness of our results.

Table 4: Expected forecast error tests

	Pre-SOX			Post-SOX		
Quintile	$T_{(G)}$	$T_{(S)}$	No.obs	$T_{(G)}$	$T_{(S)}$	No.obs
1	0.000	0.000	2526	0.000	0.000	2426
2	0.001	0.003	2616	0.000	0.000	2498
3	0.001	0.002	2447	0.002	0.000	2398
4	0.002	0.000	2294	0.01	0.006	2498
5	0.67	0.078	2294	0.007	0.000	2202

The null: $E(e_{i,t}\,|c_{i,t} = c\ ) = c\ \forall c \in C$

The numbers are the p-values of Gozalo ($T_{(G)}$) and Stute ($T_{(S)}$) statistics. For $T_{(G)}$ the choice of bandwidth is based on cross-validation The significance of $T_{(S)}$ is tested by using "wild bootstrap" with 500 replications. Each test is conducted for both pre- and-post SOX period for each portfolio

The results are presented in Table 4. For each variance ratio-based portfolio we present the resulting p-value for each of the abovementioned tests for each sub-period. As it can be seen from the table, for all portfolios the null is strongly rejected, both before and after the Sarbanes-Oxley legislation, suggesting that in the post-legislation period the consensus forecasts still do not yield the "best" estimates of actual earnings. These findings also suggest that the analysts' forecasts can be significantly improved by adding to the latter the correction factor $E(e_{i,t}\,|c_{i,t}\,) - c_{i,t}$. Moreover, the analysis of the behavior of this correction factor will provide us the clues on whether the performance of the analysts has changed in the post-SOX period. In particular, if the analysts' performance has improved following the legislation of the SOX we would expect to observe a decline in the magnitude of the correction factor. Thus, we turn now to the analysis of whether the analysts' performance has changed following the enactment of the SOX.

Q.5. Has there been a structural shift in the conditional dynamics of the analysts' forecasts errors following the introduction of SOX, and if so, in which direction?

Analysts' performance- a visual inspection

To gain some preliminary insight into the dynamics of the analysts' forecast errors before and after the enactment of the SOX reform we plot the estimated correction factor, $\hat{E}(e_{i,t}\,|c_{i,t} = c) - c$,versus the consensus forecast c for each value of c lying in the range of ($q_{c,0.05}$,$q_{c,0.95}$) in Figures 4 to 6, with $q_{c,0.05}$ ($q_{c,0.95}$) denoting the 5% (95%) sample quantile of the consensus forecasts distribution. The estimated correction factor is presented for the groups of variance ratio-ranked portfolios, where for each group we present the estimated correction factor before and after the SOX has been signed into law separately along with the corresponding uniform confidence bands. Starting with the analysis of the correction factor for the low variance-ratio firms, which is presented in Figure 5.4, it appears that there has been a structural shift in the forecast error-consensus forecast relationship. Surprisingly, however, it appears that the magnitude of the correction factor has increased, suggesting that in the post-SOX act period the analysts' forecasts on average became *less* accurate. In addition, two interesting findings should be mentioned. First, the correction factor became more positive, suggesting that the analysts became more overpessimistic, or cautious. Secondly, it appears that in the post-SOX period the correction factor is substantially more pronounced for the positive forecasts, i.e., we would expect the analysts' forecasts errors to be more positive when the firm's management is reporting "good" news. An inspection of the behavior of the expected forecast error for the high variance ratio firms, presented in Figure 5.6, leads to similar conclusions. The third quintile portfolio appears to be the only exception, where it seems to be hard to reach any specific conclusions regarding the change in direction of the bias (see Figure 5.5). However, the shift in the correction factor is substantially more pronounced for the low variance-ratio stocks, that is, for the firms with more pronounced bias-variance trade-off by the analysts, suggesting that the analysts following these firms became substantially more cautious when the firms' management discloses "optimistic" information.

To study further the nature of the bias we are also interested in studying the relationship between the expected forecast error and the forecast uncertainty, and, in particular, whether this relationship has undergone any kind of structural shift, following the series of corporate scandals and the SOX legislation. Based on the underlying logic of bias-precision trade-off models we would expect the magnitude of the forecast errors to increase during the periods of higher uncertainty regarding the future earnings since the analysts are more likely to request additional information from the firm's management when the earnings exhibit a high degree of variation. Moreover, if the source of the structural shift is the SOX act, which made the information regarding the financial and economic conditions of the firm more accessible, we would expect to see a link between the forecast errors and the forecast uncertainty becoming weaker, since due to an increase in the information transparency we would expect the analysts forecasts' to become less dependent on the information provided by the management. On the other hand, it is also possible that a structural shift (if detected) is due to the corporate scandals which were related to the misreportings and the earning manipulations of the management, such as the Enron and Worldcome inquiries. In this case we would expect the analysts to become more cautious in their forecasts, which could lead to an increase in the forecast errors. Also, the link between the forecast errors and the forecast uncertainty is expected to become stronger, since, following the scandals, we would expect the analysts to become more cautious during the turbulent periods compared to the pre-SOX period.

Figures 5.7 to 5.9 provide some visual impression on the relationship between the analysts' forecast errors and the earnings forecast uncertainty, where, as a proxy of uncertainty, we take the analysts' forecast spread $s_{i,t}$, which we define as the highest forecast minus the lowest forecast for the last month before the actual earning is announced for each firm-quarter observation. As before, we plot a non-parametric estimate of the expected forecast error, $\hat{E}(\epsilon_{i,t}\,|s_{i,t} = s)$, for each value of s lying in the range of $(q_{s,0.05}$,$q_{s,0.95})$ for the variance-ratio ranked portfolios. A number of interesting findings should be mentioned. First, by observing the overall level of the analysts' forecasts errors it seems that the latter was positive, that is, in both periods, on average, analysts tended to submit overpessimistic forecasts. This finding is consistent with the results obtained from the inspection of Figures 4-6. Interestingly, the magnitude of the forecast errors appears to be related to the level of the uncertainty regarding the future earnings, measured by the forecasts spread, a finding which is consistent with the results reported by Imhoff and Lobo (1990). Moreover, we find that the forecast error is likely to increase during the turbulent periods, a finding, which cannot be attributed to the bias-variance trade-off model of Lim (2001), who assumes that firms' managers prefer overoptimistic forecasts which would lead to the forecast errors being negative during the periods of high earnings uncertainty. On the other hand this finding is consistent with the bias-precision trade-off model if the firm's management desire is to meet or beat analysts forecasts, as reported by Degeorge *et al.* (1999).

This positive link appears to be more pronounced for the lower quintile portfolios, which is also consistent with the predictions of the bias-variance trade-off models with 'meat or beat analysts forecasts' management strategy.

However, the most intriguing results come from the comparison of the forecast error-forecast spread link in both periods. First, there is a clear visual evidence of a structural shift in the overall level of the forecast error. More specifically, we find that the overall level of the analysts' forecast errors has experienced an upward shift, a finding, which holds both for the low and high variance-ratio firms. The magnitude of the observed shift is indeed striking, ranging from 50 percent for the lower quintile to more than 100 percent for the upper quintile portfolios. Moreover, it seems that there has also been a structural change in the bias-spread relationship. Comparing the forecast error-forecast spread plots for the pre-and post-SOX periods we find that the analysts' forecast errors became substantially more positively related to the earnings uncertainty. This shift is also substantially more pronounced for the low-quintile portfolios, for which the estimated forecast error-forecast spread curve turns from being moderately increasing or almost flat to substantially increasing. The shift in forecast error-forecast uncertainty link, however, is also detected for the high variance ratio portfolios, where the estimated forecast error-forecast spread curve, which in the pre-SOX period exhibited an inverted "U" shape, turned to be substantially increasing in spread.

Analysts' performance- formal tests

We start with a Gozalo-type nonparametric test described in Section 4. We test for the presence of structural shifts by using two different conditioning variables: the consensus forecast c and the forecast spread s. As for the standard Gozalo test, we calculate the value of the statistic for ten randomly chosen values of c over the range of $(q_{c,0.05}, q_{c,0.95})$ and for ten randomly chosen values of s over the range of $(q_{s,0.05}, q_{s,0.95})$.

Table 5: Structural shift tests

Quintile	$T_{(G)}$	p-value	min / max	rho$_b$	rho$_a$	t.stat	p-value
$H_0 : E_{S1}(\epsilon_{i,t} \,\vert c_{i,t}) = E_{S2}(\epsilon_{i,t} \,\vert c_{i,t})$							
1	34.44	0.0002	[0.02,13.47]	0.07**	0.194**	3.98	0.0000
2	19.76	0.031	[0.08,5.63]	0.134**	0.184**	1.59	0.11
3	17.39	0.06	[0.009,5.82]	0.087**	0.191**	3.26	0.001
4	19.35	0.036	[0.002,10.62]	0.056**	0.179**	4.14	0.0000
5	42.51	0.0000	[0.095,13.95]	0.074**	0.189**	3.72	0.0000
$H_0 : E_{S1}(\epsilon_{i,t} \,\vert s_{i,t}) = E_{S2}(\epsilon_{i,t} \,\vert s_{i,t})$							
1	515.98	0.0000	[30.54,61.87]	0.107**	0.248**	4.68	0.0000
2	102.5	0.0000	[0.77,23.64]	0.046**	0.108**	1.94	0.05
3	95.57	0.0000	[4.92,13.11]	0.007	0.062**	1.74	0.08
4	67.54	0.0000	[0.54,23.31]	0.03	0.06**	0.98	0.32
5	103.86	0.0000	[0.02,22.21]	0.005	0.07**	1.95	0.05

min/max denote minimum/maximum value of ten randomly selected Gozalo-type statistics; rho$_{S1}$ and rho$_{S2}$ denote Spearman's rho estimates for pre-and post-SOX periods Spearman's rho variance estimates are based on 1000 Monte-Carlo replications

** denotes significance at 5% level

The results are presented in Table 5. For each variance ratio ranked portfolio we test two separate null hypotheses: $H_0 : E_{S1}(\epsilon_{i,t} \,|c_{i,t} = c) = E_{S2}(\epsilon_{i,t} \,|c_{i,t} = c)$ and $H_0 : E_{S1}(\epsilon_{i,t} \,|s_{i,t} = s) = E_{S2}(\epsilon_{i,t} \,|s_{i,t} = s)$. By testing the first hypothesis, we test for the presence of a structural break in the forecast error-consensus forecast relationship, while by testing the second one we test for the stability of the forecast error-forecast uncertainty link. We start with the analysis of the forecast error-consensus forecast relationship, with the results presented in the upper panel of Table 5. Our results strongly suggest the presence of a structural shift in the forecast error-consensus forecast linking function after the SOX has been signed into law. The null of intertemporal stability is strongly rejected for the first two quintile portfolios, with somewhat weaker, though still significant, evidence of a structural break for the upper quintile. Overall, our findings suggest that a structural shift has occurred and that the latter appears to be more pronounced for the low variance-ratio firms, that is, the firms with more pronounced bias-variance trade-off by the analysts. To provide an additional insight into the nature of this shift, for each quintile we calculate the estimates of Spearman's rho between the forecast error and the corresponding consensus forecast, for both the pre- and-post SOX act sub samples. The estimates are presented in the sixth and seventh columns of the upper panel of Table 5. Starting with the pre-SOX period the results suggest that there exists a statistically significant and positive dependence between the forecast error and the consensus forecasts, suggesting that, on average, it is more likely to observe a positive earning surprise when the analysts submit high earnings estimates. In other words, the forecasts are relatively more "overpessimistic" when the firm management issues positive reports regarding the economic and financial fundamentals of the firm. This can be attributed either to the earnings management or to the analysts being more cautious when they receive too optimistic reports. However, the low magnitude of the estimates suggests that the economic significance of this dependence is somewhat limited, with the second quintile being the only exception. The results dramatically change in the post-SOX period, where for all portfolios Spearman's rho experienced a sharp increase in its value. The magnitude of increase is indeed dramatic, ranging between 40 percent for the second quintile and more than 200 percent for the 4-th quintile.

Next, we study the results of the structural shift test for the forecast error-forecast uncertainty link. The results of the test using the critical values of the χ^2_{10} distribution suggest that the null of the intertemporal stability is strongly rejected for any reasonable significance level. The results are similar when we use the critical values implied by the Bonferonni upper bound. This confirms the visually based findings, which indicated an upward shift both in the overall level of the forecast errors and in the forecast errors-forecast spread link. These findings gain an additional support from the analysis of Spearman rho estimates between the earnings surprise and the forecast spread. For the pre-SOX period only for the first two quintiles we find a significant and positive dependence between the bias and the uncertainty, while for the rest of the firms the estimates are neither statistically nor economically significant. However, our findings dramatically change as we move to the post-SOX period, where for all the quintiles we find a statistically significant and positive relationship between the earnings surprise and the spread. As with the bias-consensus link, the changes in Spearman's rho are indeed striking and are especially pronounced for the lower quintile portfolios.

We formally test the null $\text{rho}_{S1} = \text{rho}_{S2}$ via standard pairwise t-test. This test requires an estimate of the asymptotic variance of the estimators of both rho_{S1} and rho_{S2}. Though a closed and compact formula for the asymptotic variance exists, it is hardly suitable for practical applications, since it requires estimation of high-dimensional integrals (see, for instance, Schmid and Schmidt (2006)). Instead, these authors propose to use bootstrap based estimates, an approach we shall adopt in this study as well. In the last two columns of Table 5 we report the test statistics and the corresponding p-values for each quintile. Overall, our findings indicate that the forecast error-consensus forecast and forecast error-forecast uncertainty links became both statistically and economically significant in the post-SOX period. These findings suggest that, following a series of corporate scandals, analysts became substantially more cautious in forming their forecasts.

SOX or Regulation FD - a Robustness Check

While we find a substantial evidence of structural shifts in the analysts' forecasts bias in the post-SOX period, the remaining question is whether this shift is due to the corporate scandals or, perhaps, it can be attributed to some other event which occured during our sample period. A natural candidacy for such event is the Regulation Fair Disclosure act (FD) enacted on October 23, 2000. Regulation FD prohibits corporations from privately disclosing material information to a subset of investors or securities markets professionals, e.g. analysts, without simultaneously disclosing the same information to the public. Since the implementation of FD is likely to be associated with changes in the earnings-related information environment, this legislation could also lead to structural shifts in forecasting performance of the analysts. Thus, to examine the robustness of our results we conduct the same tests with the alternative partitioning of our sample period. More specifically, we partition the whole sample into three sub-samples: January 1998-October 2000 (encoded Pre-FD), November 2000-July 2002 (encoded Post-FD/Pre-SOX), August 2002-June 2006(encoded Post-SOX). By partitioning the pre-SOX period into pre-FD and Post-FD/Pre-SOX periods we seek to disentangle the impact of Regulation Fair Disclosure act from the potential effect of the SOX act and the preceeding corporate scandals. For each sample period we conduct the same structural shift tests we conducted for the two sub-sample partitioning. In particular, while testing for the structural shift we test separately for the presence of the structural shift between the pre-FD and post-FD/pre-SOX periods, and between post-FD/pre-SOX and post-SOX periods. A structural break in the analysts' forecast bias between pre-FD and Post-FD/Pre-SOX periods can be attributed to the impact of FD regulation, while a shift in the forecast bias between the post-FD/pre-SOX and post-SOX periods is likely to be attributed to the impact of the SOX.

We start with a visual inspection of the forecast error-consensus forecast and the forecast error-forecast spread plots depicted in Figures 5.10-5.15. Each figure depicts a nonparametric estimate of the forecast error-consensus forecast or the forecast error-forecast spread link for the pre-FD, post-FD/pre-SOX and post-SOX periods. A number of interesting findings should be mentioned. First, there is an upward shift in the overall level of the analysts' forecast bias, a finding which suggests that over time analysts became more "overpessimistic" regarding future firms' earnings. The shift in the overall level of bias, that is, the shift of the "intercepts" of the estimated curves, is pronounced both for the forecast error-consensus forecast and the forecast error-forecast spread links. This is consistent with findings of Brown (2001), who reports a similar trend in the earnings surprise, though for the earlier period. Second, no visual shift in the forecast error-consensus forecast link can be detected between pre-FD and post-FD/pre-SOX periods. The findings are similar for the forecast error-forecast spread link. On the other hand, we do find some evidence of a structural shift in both forecast error-consensus forecast and forecast error-forecast spread relations between the post-FD/pre-SOX and post-SOX periods. For the forecast error-forecast spread link a shift is more pronounced for the firms with low variance ratio, which emphasizes, though informally, the need to control for the bias-variance trade-off. Overall, visual inspection informally suggests that the structural shifts detected in the analysts' bias seem to occur in the post-SOX period and are unlikely to be attributed to the Regulation FD.

Table 6: Structural shift tests - 3-period partition

Table 6.1: Forecast error-consensus forecast tests

	pre-FD vs post FD/pre-SOX			post FD/pre-SOX vs post-SOX		
Quintile	$T_{(G)}$	p-value	min / max	$T_{(G)}$	p-value	min / max
1	16.31	0.09	[0.44,8.59]	40.39	0.0001	[0.073,15.84]
2	4.65	0.91	[0.02,1.48]	15.65	0.11	[0.14,4.66]
3	20.46	0.025	[0.006,8.45]	32.67	0.0003	[0.89,6.83]
4	21.34	0.02	[0.009,3.82]	43.51	0.0000	[0.002,16,39]
5	6.31	0.79	[0.02,2.57]	53.15	0.0000	[0.18,11.79]

Table 6.2: Forecast error-forecast spread tests

1	104.83	0.0000	[1.38,18.31]	116.49	0.0000	[10.39,13.56]
2	2.62	0.98	[0.09,1.23]	139.48	0.0000	[3.84,15.62]
3	17.52	0.063	[0.68,3.11]	113.67	0.0000	[3.48,19.59]
4	37.66	0.0001	[1.78,5.74]	119.41	0.0000	[8.16,14.94]
5	16.87	0.08	[0.06,3.56]	178.01	0.0000	[11.62,21.8]

In this table we present the results of the Gozalo-type structural shift tests for the 3-period sample partition. We test for structural shifts in the post-FD/pre-SOX and the post-SOX periods. min/max denote minimum/maximum value of ten randomly selected Gozalo-type statistics. $T_{(G)}$ denotes the value of statistic.

Next, we turn to the formal structural shift tests. The results of the nonparametric Gozalo-type test are presented in Table 6. The upper panel of Table 6, Table 6.1, presents the results of the structural shift test applied to the forecast error-consensus forecast relation. The results of the structural shift tests for the pre-FD versus post FD/pre-SOX periods suggest that there was a structural shift in the forecast error-consensus forecast relation for the third and forth quintiles. There is also strong evidence of a structural shift following the enactment of the SOX for all but second quintile, where the results are marginally significant. The results of the structural shift tests applied to the forecast error-forecast spread relation, reported in Table 6.2, depict a similar picture. There is a significant evidence of a structural shift in both post-FD/pre-SOX and post-SOX periods. However, these shifts can also be attributed to the overall shift in the analysts' forecast bias. Thus, to study further the nature of these structural shifts we study the estimates of Spearman's rhos.

Table 7: Structural shift test - 3-period partition

Table 7.1: Forecast error-consensus forecast tests

Quintile	rho_1	rho_2	rho_3	$t_{rho_1=rho_2}$	p-value	$t_{rho_2=rho3}$	p-value
1	0.048*	0.108**	0.18**	1.46	0.14	1.9	0.057
2	0.165**	0.089**	0.175**	-1.89	0.06	2.21	0.027
3	0.069**	0.083**	0.186**	0.334	0.738	2.64	0.008
4	0.051**	0.046	0.179**	-0.09	0.096	3.46	0.0005
5	0.124**	0.005	0.188**	-2.74	0.007	4.54	0.0000
Table 7.2: Forecast error-forecast spread tests							
1	0.072**	0.168**	0.248**	2.34	0.019	1.98	0.047
2	0.065**	0.049*	0.108**	-0.36	0.76	1.59	0.09
3	0.005	0.02	0.062**	0.47	0.64	0.72	0.47
4	0.03	0.019	0.06**	-0.31	0.82	1.06	0.28
5	0.0002	0.013	0.07**	0.28	0.78	1.35	0.17

In this table we present the results of the structural shift test for the forecast error-consensus forecast relation and forecast-error forecast spread relation for the 3-period sample partition. rho_1, rho_2, and rho_3 are the Spearman rho estimates for the pre-FD, post-FD/pre-SOX, and post-SOX periods. The following null hypotheses are tested: H_0 :rho_1 =rho_2, H_0 :rho_2 =rho_3 where $t_{rho_1=rho_2}$ and $t_{rho_2=rho_3}$ are the corresponding t-statistics, respectively.

The estimates of Spearman's rhos as well as the t-statistics of the structural shift tests and the corresponding p-values are reported in Table 7. Here rho_1, rho_2, and rho_3 denote Spearman's rho estimates for the pre-FD, post-FD/pre-SOX and post-SOX periods respectively. First, consistent with the results of the nonparametric tests reported in Table 6 we find some evidence of structural shifts in the forecast error-consensus forecast link in the post FD/pre-SOX period. Secondly, and more important, we find a strong evidence of a structural shift in the forecast error-consensus forecast relation in the post-SOX period. More specifically, we find the upward shift in the estimates of Spearman's rho, a shift which is both statistically and economically significant for all the quintiles. Turning to the forecast error-forecast spread link, we find almost no evidence of a structural shift with a first quintile being the only exception. On the contrary, we find an increase in Spearman's rho estimates in the post-SOX period for all the quintiles. For the first two quintiles the shift is also statistically significant. Overall, these results support the robustness of our findings, that there has been a structural shift in the analysts' forecast bias following the enactment of the SOX.

5.6 Conclusions and Topics for Further Research

In this paper we examine the implications of the Sarbanes-Oxley reform of 2002 for the informational efficiency of the US stock market and the performance of the stock market analysts. To the best of our knowledge, this is the first paper that addresses these issues and the questions raised and studied in this paper are of major importance, both for the policy makers and practitioners.

To study the impact of the SOX reform on the informational market efficiency we estimate the partial adjustment model with noise of Amihud and Mendelson (1987) for all the firms listed on the NYSE/AMEX during the last decade. By applying an endogenous structural break tests of Andrews (1993) and Andrews and Ploberger (1994), we find 2002 to be the year when a lions share of the structural breaks in the speed of adjustment occurred. Further tests indicate that, following the enactment of the SOX reform, the average speed of adjustment to the new information has dramatically increased, suggesting that, following the legislation, investors incorporate more rapidly the information released by the firms in the stock prices, thus, making the US stock market more informationally efficient.

We also study the implications of the Act of 2002 for the accuracy of the analysts' forecasts. By applying non-parametric tests to the large span of I/B/E/S forecasts and actual earnings data, we find that both before and after the reform the analysts' forecasts were significantly "overpessimistic". Moreover, we find that in the post-SOX period the degree of the "overpessimism" has not declined, but rather increased. An increase is especially pronounced during the turbulent periods and/or when "good" news is released. These findings suggest that an increase in the magnitude of the forecast errors can be attributed to the analysts becoming more cautious following the series of corporate scandals when severe earnings overestimations were uncovered.

Our findings also propose a number of promising directions for further research. First, it may be interesting to dichotomize the analysts' forecasts into those submitted by the analysts who work for the underwriting firms and those who do not. Several studies find that the former are, in general, "overoptimistic", and, therefore, it is quite possible that their overoptimism on the one hand, will be balanced by the impact of the corporate scandals on the other hand, leading to an increase in the analysts' forecasts accuracy. Secondly, our findings suggest that the stock market investors became more efficient in incorporating new information while the picture is reverse for the analysts, suggesting that the importance of the analysts' forecasts for the investors' valuation of the firm, in particular, using the consensus forecasts as a proxy for the investors (market) expectations, seems to be overstated. An alternative explanation is that the investors are sophisticated enough to correct for the analysts' bias, which seems to be a promising research direction. Finally, our results suggest that while in a short run investors are underreacting, the degree of the underreaction. following the reform of 2002 seems to decline. Therefore, it will be interesting to compare the profitability of "momentum" based strategies both before and after the reform has been signed into law.

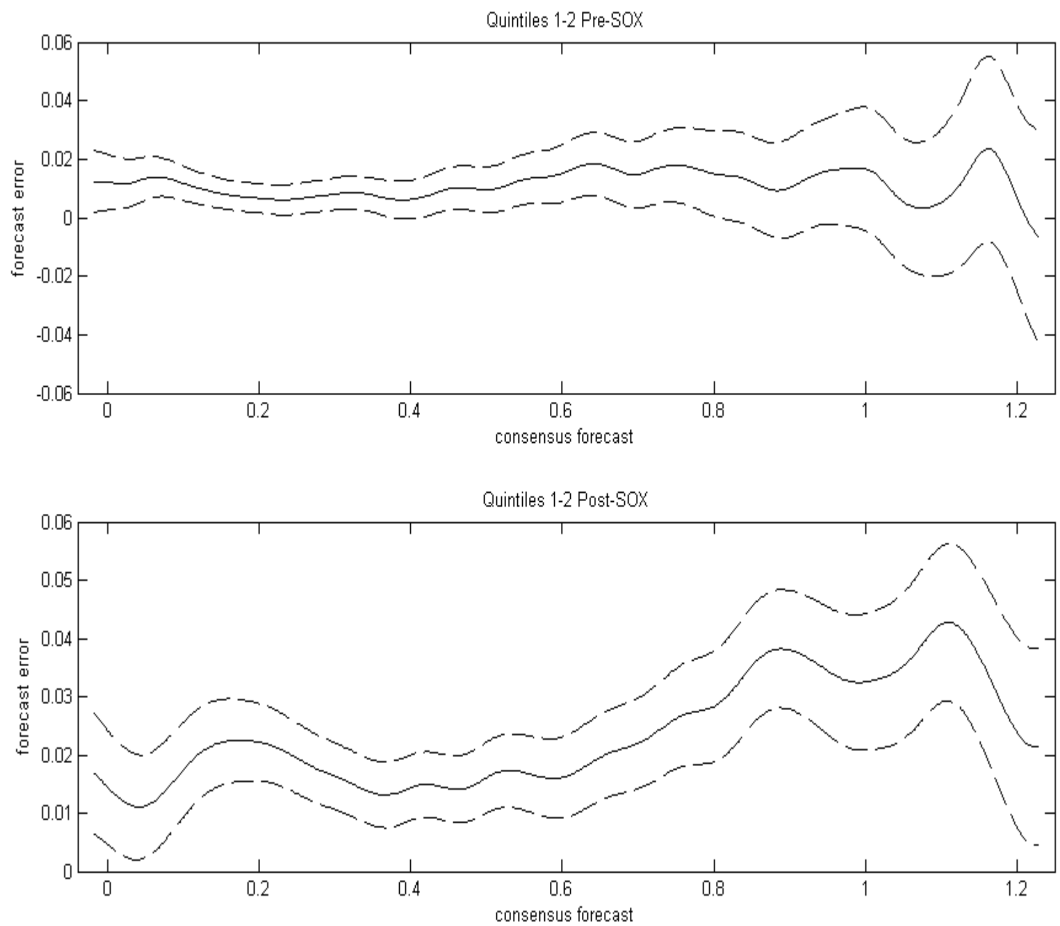

Figure 5-4: Forecast error vs consensus forecast before and after the enactment of teh SOX. Dashed lines denote 95% uniform confidence bands.

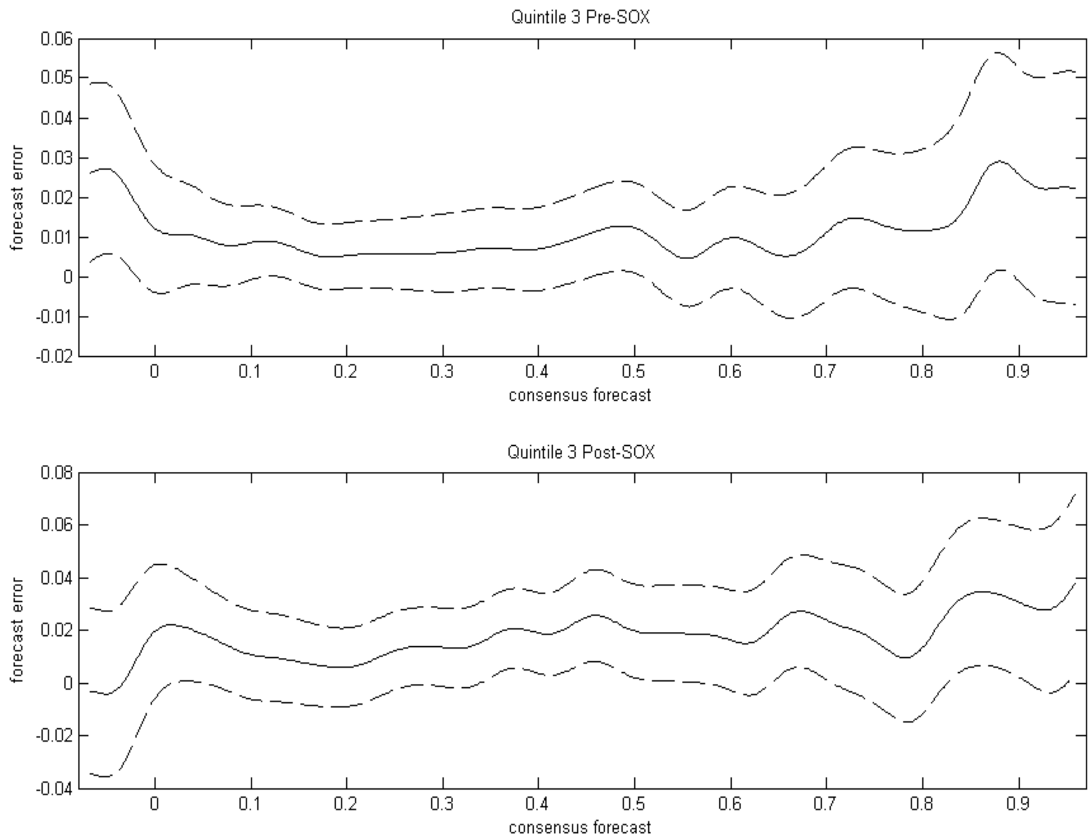

Figure 5-5: Forecast error vs consensus forecast before and after the enactment of the SOX (*continued*)

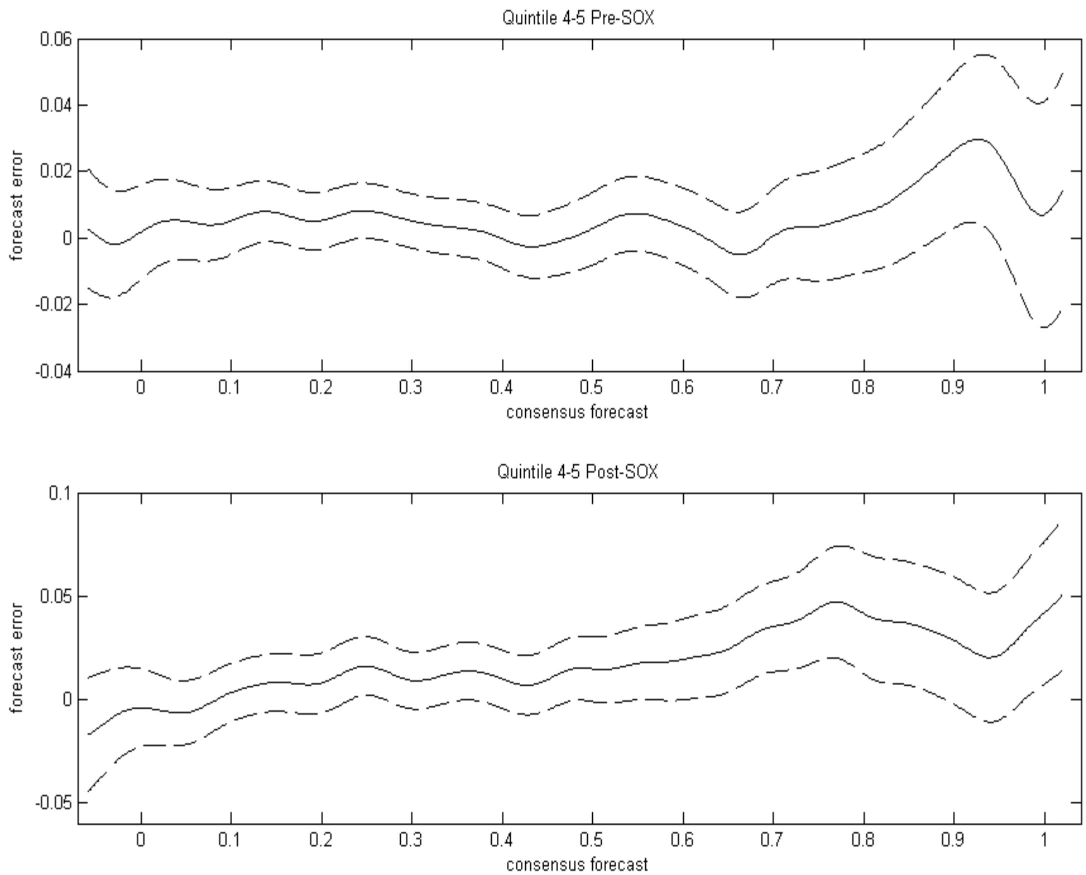

Figure 5-6: Forecast error vs consensus forecast before and after the enactment of the SOX (*continued*)

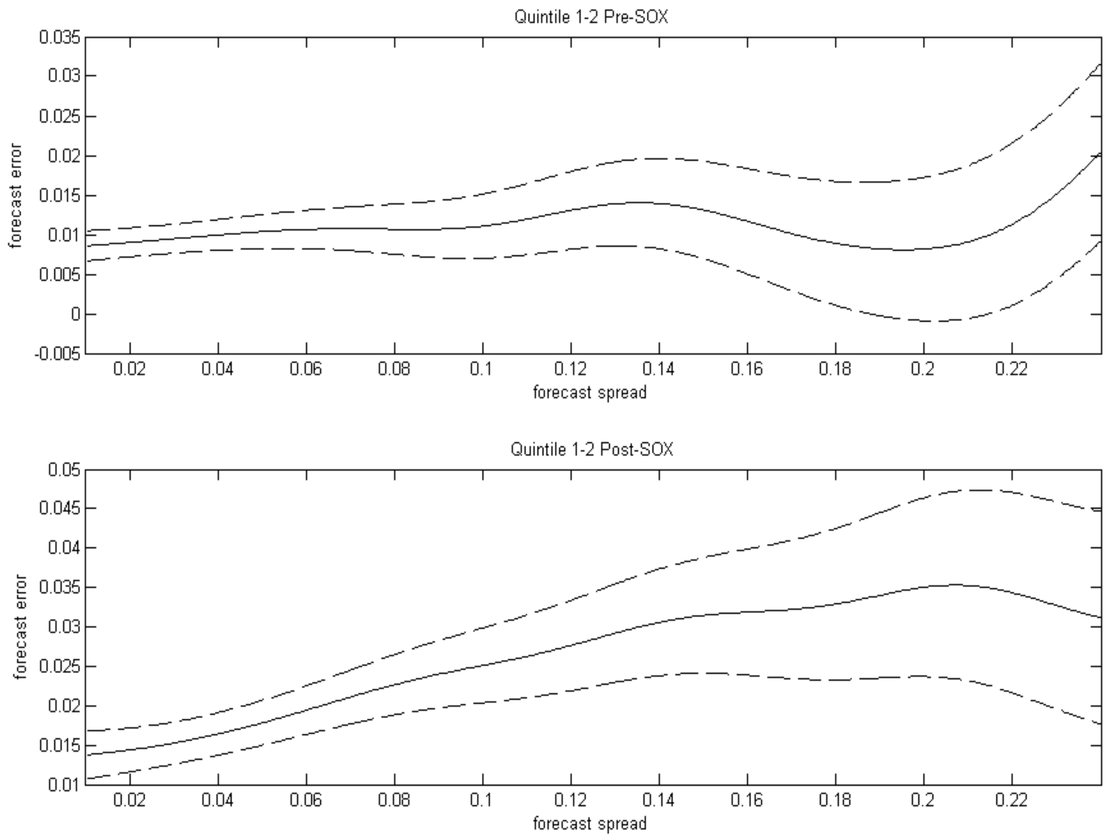

Figure 5-7: Forecast error vs forecast spread before and after the enactment of the SOX. Dashed lines denote 95% uniform confidence bands.

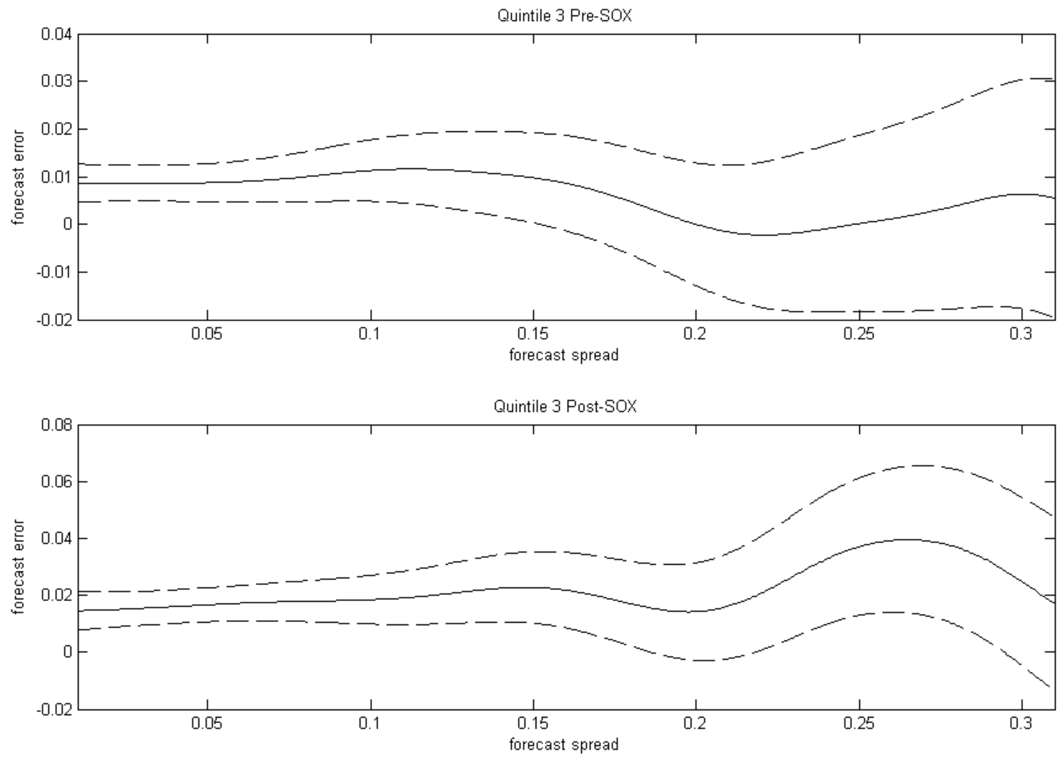

Figure 5-8: Forecast error vs forecast spread before and after the enactment of the SOX (*continued*)

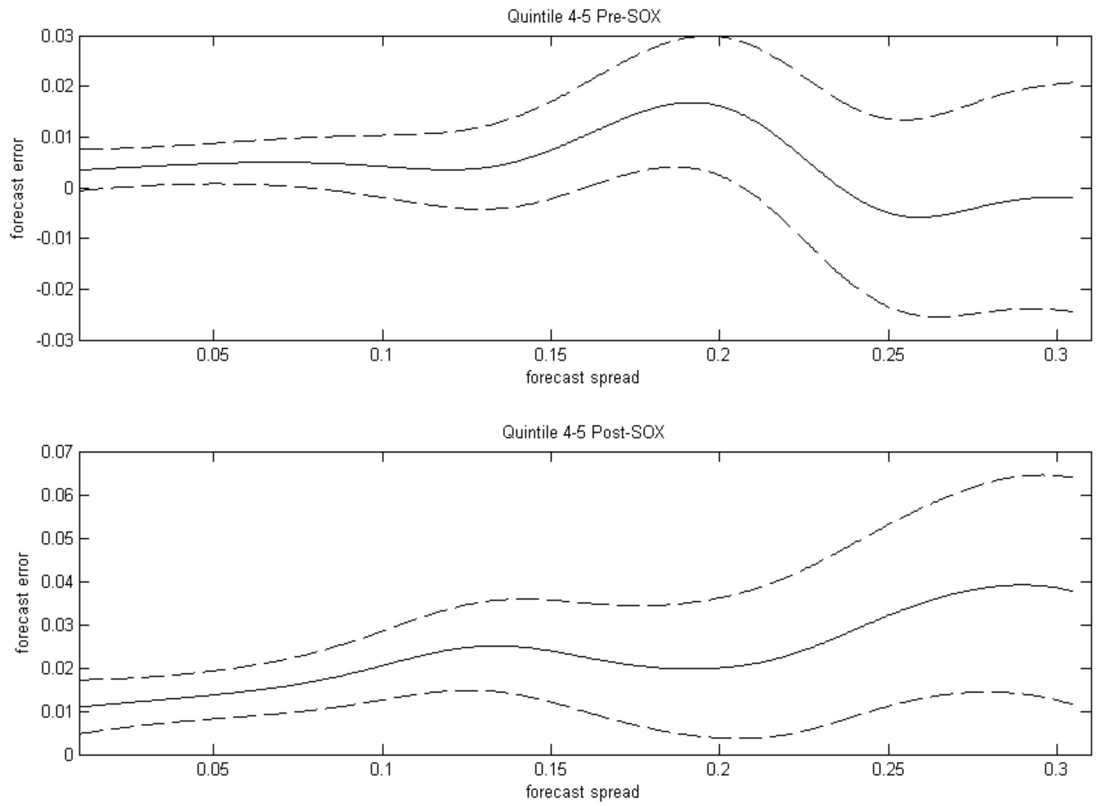

Figure 5-9: Forecast error vs forecast spread before and after the enactment of the SOX (*continued*)

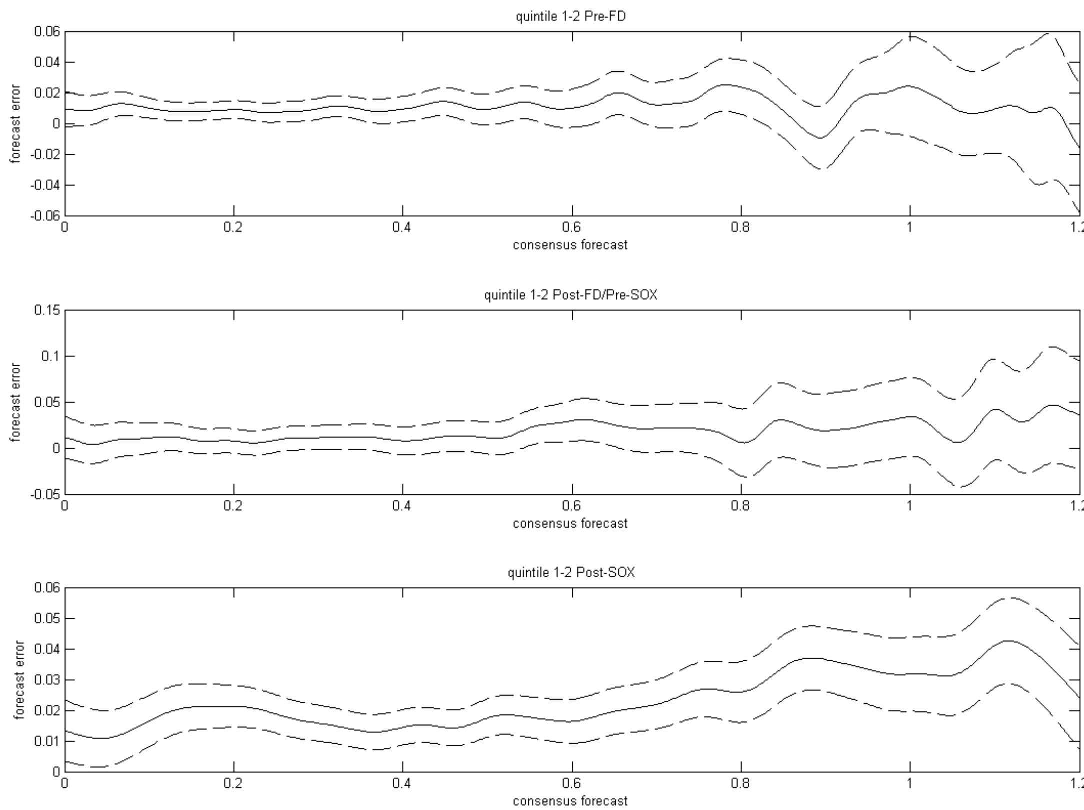

Figure 5-10: Forecast error vs consensus forecast - 3-period partition. Dashed lines denote 95% uniform confidence bands.

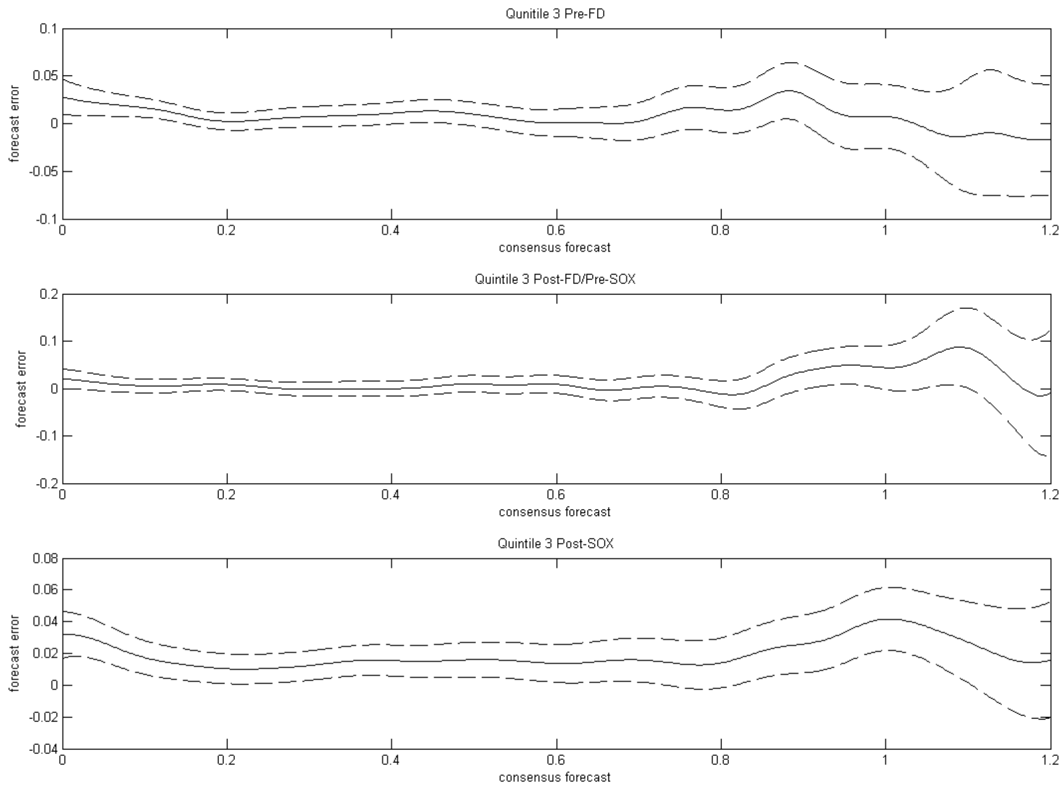

Figure 5-11: Forecast error vs consensus forecast - 3-period partition (*continued*)

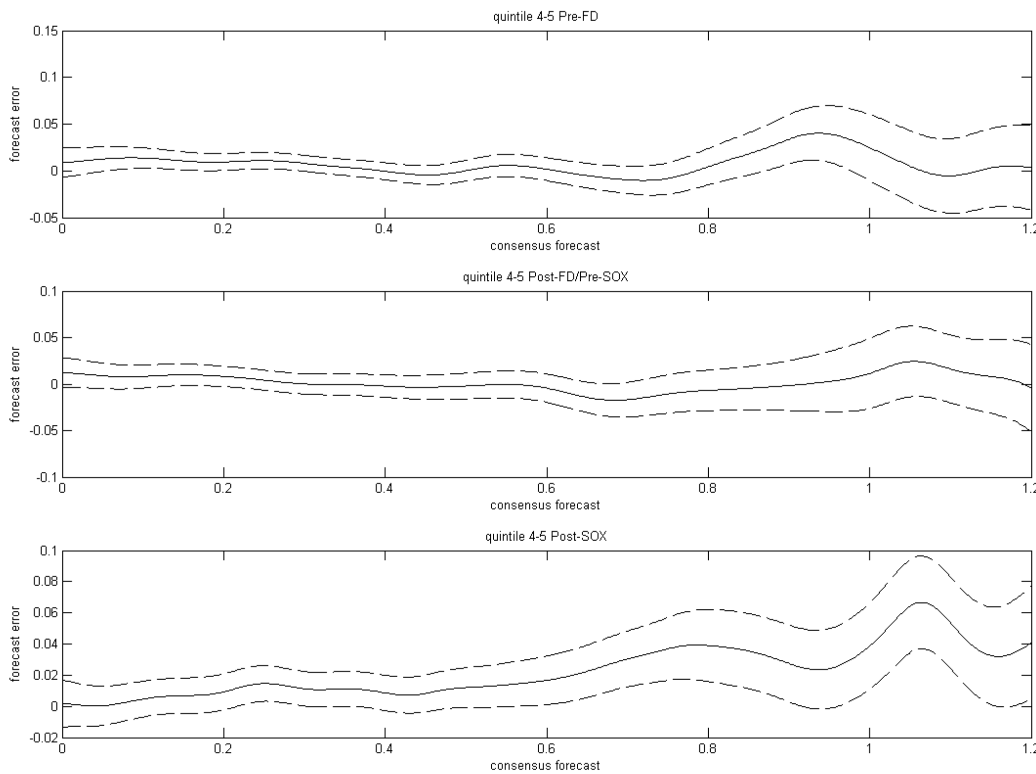

Figure 5-12: Forecast error vs consensus forecast - 3-period partition (*continued*)

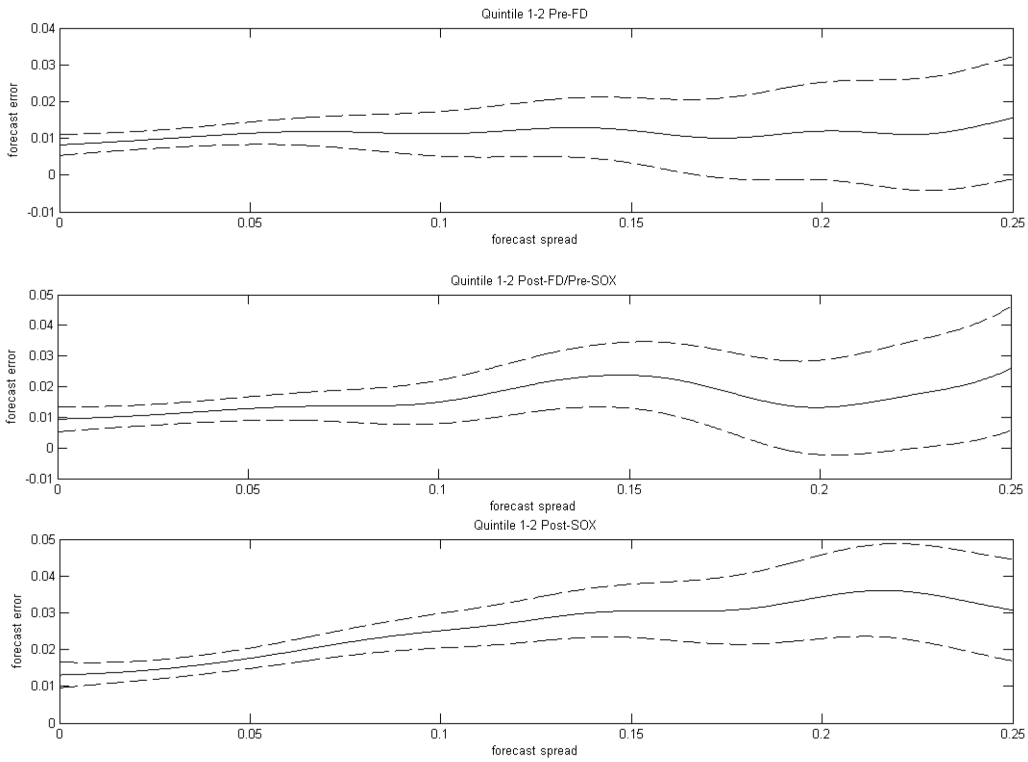

Figure 5-13: Forecast error vs forecast spread - 3-period partition. Dashed lines denote 95% uniform confidence bands.

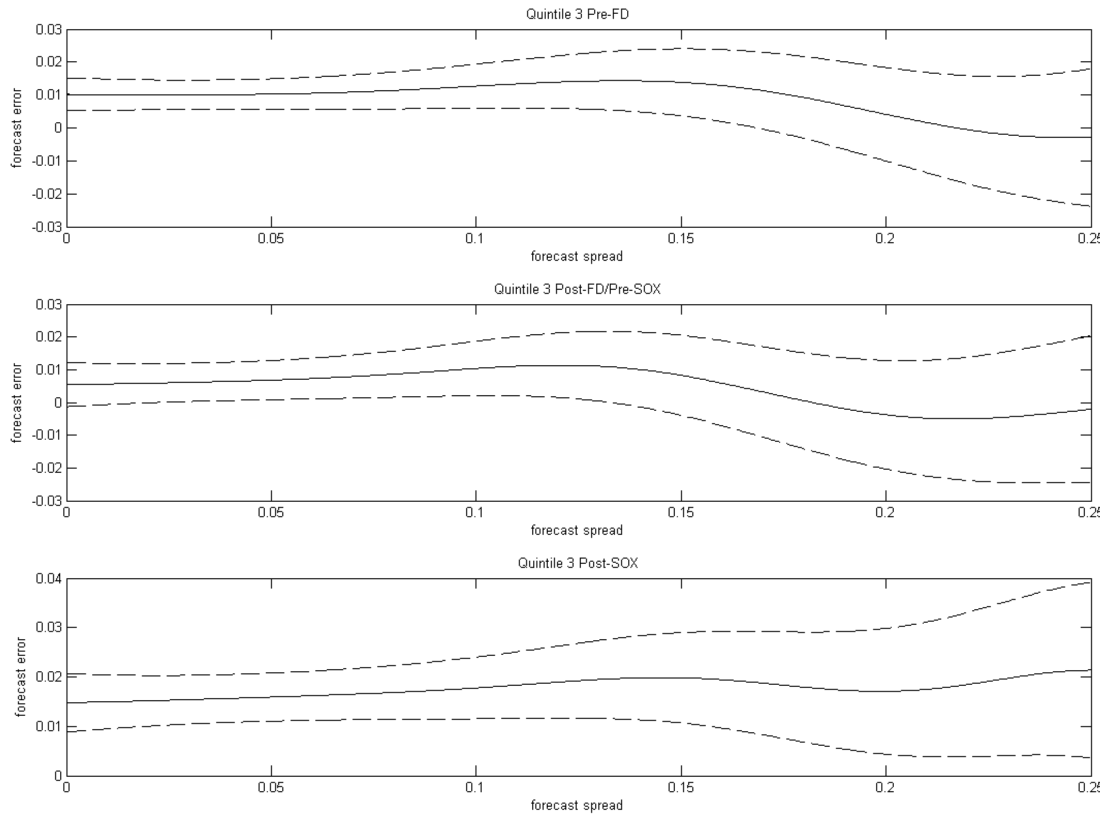

Figure 5-14: Forecast error vs forecast spread - 3-period partition (*continued*)

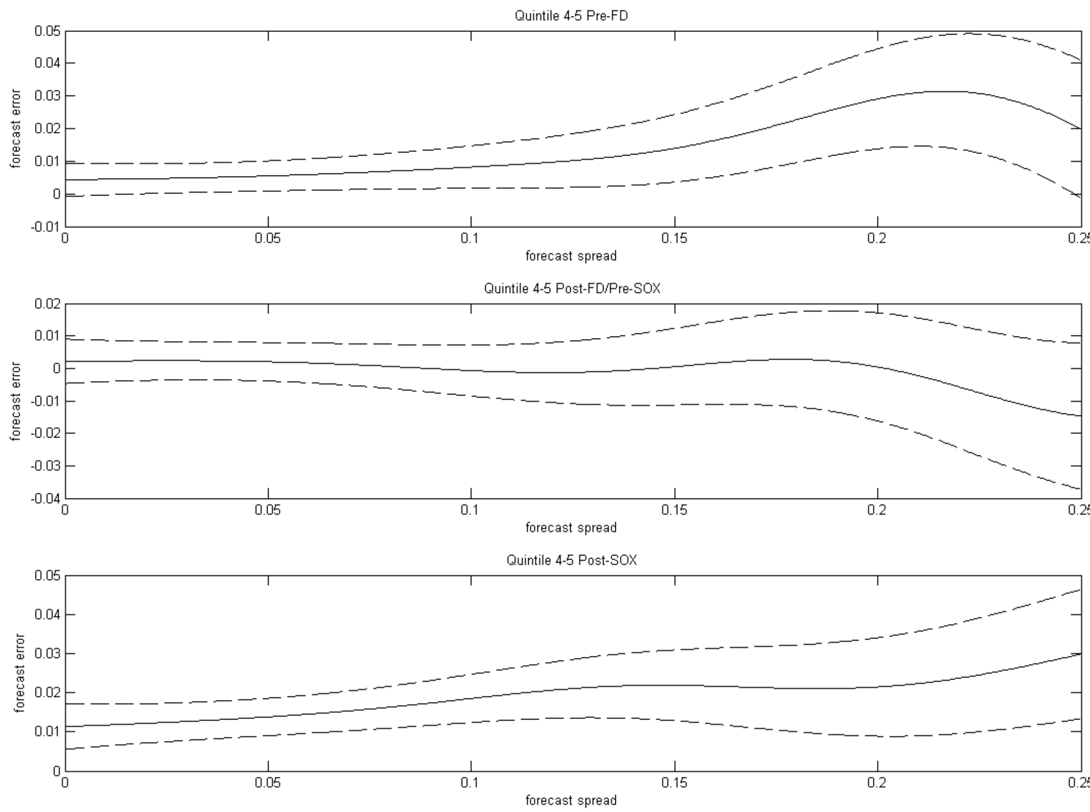

Figure 5-15: Forecast error vs forecast spread - 3-period partition (*continued*)

Chapter 6

Friday Earnings Announcements and the Earnings-Returns Relation: A Temporal Analysis

6.1 Introduction

Strategic timing of earnings announcements is one of the most widely discussed issues in both the finance and accounting literature. Understanding the links between the timing and the nature of the earnings announcements is of great importance, both for analysts as a means of improving their forecasts and for investors in making their investment decisions. Another related but not less important issue is the link between the timing of the earnings announcement and the earnings-returns relation. Understanding this link is particularly important for the firm's management who would prefer to moderate the impact of "bad" news on the value of the firm.

In this paper we study the evolution of the "Friday effect" over time. By this term we name two interrelated issues. The first is the alleged tendency of firms to report "bad" news on Fridays, while the second is that stock prices are believed to be less sensitive to the Friday earnings announcements compared to those released during the rest of the week. We focus on the following issues:

- Do firms tend to report "bad" news on Fridays?

- If the answer is "yes", was this strategy persistent over time?
- Are investors aware of this strategy and, if so, what are the implications for the earnings-return relation and its evolution over time?

These questions are particularly important in light of a rapid increase in the information coverage over the last three decades. An increased accessibility of information makes it more difficult for the companies to "burry" unfavorable news by releasing the latter close to the weekends and/or after the market is closed. On the other hand, the enhanced informational coverage will also make the investors learn about this strategy. Therefore, if investors did become aware of this strategy we may expect the benefits from shifting "bad" news releases close to the weekends to disappear over time.

Our findings suggest that over the period 1989-2006 firms have systematically reported more "bad" news on Fridays compared to other trading days. Also, we find that the earnings-returns relation has undergone a structural shift over time. More specifically, while for the late 80-s and the beginning of the 90-s the impact of Friday earnings announcements on stock returns was weaker than during the rest of the week, the picture reversed during the last ten years, with stock returns becoming more sensitive to Friday announcements. Curiously, the shift is more pronounced for negative earnings surprises. Finally, we find that the magnitude of the "Friday effect" in the earnings-returns relationship is inversely related to the quality of the informational disclosure. Overall, these results suggest that the firms' management tendency to report "bad" news on Fridays is related to the investors' distraction as the weekend approaches. Moreover, based on our findings we conclude that investors learned about this tendency and, therefore, the benefits from shifting announcements of "bad" news to Fridays seem to disappear over the last two decades.

The remainder of this paper is organized as follows. In Section 6.2 we briefly review some of the existing literature on the subject, Section 6.3 describes the data. In Section 6.4 we study the distributional properties of the earnings surprises and their evolution over time. In Section 6.5 we test for the presence and examine the dynamics of a "Friday effect" in the earnings-return relation. Finally, in Section 6.6 we present our concluding remarks and discuss some directions for further research.

6.2 Literature Review

A substantial body of the literature on the earnings announcements documents that there exists a relationship between the timing of an earnings report and the nature of the news released in that report. Givoly and Palmon (1982), Chambers and Penman (1984), and Kross and Schroeder (1984), using a sample of earnings announcements drawn from the 1970's, find that if a firm releases its earnings report earlier than expected its stock price rises, on average, while if the report is released with delay, the stock price declines. A more recent study by Begley and Fischer (1998) supports their findings for the period of the 1980-s and early 1990-s.

There is also an increasing amount of evidence concerning the relation between the day of the week and the nature of the earnings announcements. In particular, a number of studies find that the firms tend to release more bad news close to and during the weekend. Penman (1987), who uses a sample of earnings reports for the period of 1971-1982, finds some evidence that reports released during the middle of the week are more likely to yield significantly more positive returns compared to those released on Friday or Monday. Using a sample of earnings and dividend announcements over the period 1981-1985, Damodaran (1989) finds that the reports released on Fridays are more likely to contain "bad" news and to be associated with negative abnormal returns, than those on other weekdays. Della, Vigna, and Pollet (2005) use a sample of earnings announcements for the period 1995-2004 to study the behavior of earnings announcements and the response of returns to the earnings surprises on Friday and other weekdays. They report Friday announcements being associated with a 45 percent higher probability of a negative earnings surprise and a 50 basis points lower abnormal returns. Also, they find that Friday announcements have less immediate and a more delayed stock return response. A continued dominance of "bad" news on Fridays is reported by Bagnoli, Clement, and Watts (2006) for the period 2000-2003.

A number of theories have been proposed to rationalize the observed pattern of the earnings announcements' timing. Trueman (1990) studies the optimal timing of the information release in a two-period model with many firms and risk-neutral investors. The firms are assumed to be owned by the managers during the first period, who then sell shares in their firms to the investors before the end of the second period. The managers are assumed to have flexibility to shift the recognition of economic earnings as accounting income form the second period to the first.

Trueman (1990) shows that the delay in reporting the "bad" news can be either due to earnings management or due to the managements' desire to first observe other firms' earnings. Gennotte and Trueman (1996) study the optimal intraday timing of earnings announcements. They propose a two-period model where a distinction is made between noise traders and informed traders. The latter are better able to make predictions regarding the future profitability of the firm than the former and submit their orders immediately after an announcement is released. A basic result of this model is that the impact of a disclosure is expected to be stronger if it occurs during trading hours than after the market is closed.

In this paper we conduct a temporal analysis of the distribution of earnings news and the properties of the earnings-returns relation over the last two decades. Importantly, we make a distinction between announcements released on Fridays and those released on other weekdays, to control for the "Friday" effect, reported by previous studies. By means of both a nonparametric and a parametric analysis we study and compare the distributions of Friday and non-Friday earnings surprises, the response of stock returns to Friday versus non-Friday earnings announcements, and how they evolved over the last two decades. The contribution of this paper is twofold. First, we extend the existing earnings-returns relation literature. In particular, this paper makes an important contribution to a rapidly growing strand of literature studying the time evolution of the earnings surprise and the earnings response function. These studies include Brown (2001), who conducts a temporal analysis of median earnings surprise, Landsman and Maydew (2002), who study the informational content of the earnings announcements for the last three decades, and Collins, Li, and Xie (2005), who report that over time stock returns became more sensitive to the Street earnings reported by I/B/E/S, among others. However, none of these studies conducts a temporal analysis of the "Friday effect". Thus, the first purpose of this paper is to fill this gap in the earnings-returns relation literature.

Second, our paper contributes to the discussion regarding the reasons for strategic timing of earnings announcements. The conventional wisdom suggests that the investors become more distracted as the weekend approaches. This, in turn, leads to a lower quality of decision making and an immediate impact of earnings surprises on stock returns on Fridays becoming less pronounced. This idea has been formalized by Hong and Stein (1999), who suggest that individuals are able to "process" only some subset of the available public information. On the other hand, an increased intensity of the media coverage as well as the academic literature is likely to draw the investors' attention to the "Friday effect" phenomenon. As a result, investors may gradually learn about the firms' announcement strategies which, in turn, may cause the "Friday effect" in the earnings-returns relation to disappear, as it happened to other market "anomalies" (Schwert, 2003). But then the benefits from shifting the announcement of "bad" news to Fridays are likely to dissipate over time. Therefore, studying the dynamics of the "Friday effect" over time yields important practical implications for the announcement policies of firms.

6.3 Data Description

We collect quarterly earnings announcements for all firms listed on the US stock markets over the period 1989-2006. Each firm-quarter observation includes actual earning, median analysts' forecast (both in terms of US dollars per share), earnings announcement dates, and the number of analysts' forecasts submitted.[1] This data has been obtained from the Institutional Brokerage Estimate System (I/B/E/S). Next, for each firm-quarter observation we match the stock return at the announcement day, the return on the equally-weighted market portfolio the day the announcement was made, and the closing stock price from the day before the earnings announcement. This data has been obtained from the Center for Research in Security Prices (CRSP) tapes. Our initial sample consists of 262,823 firm-quarter observations, with a minimum of 5,856 observations for 1986 and a maximum of 18,390 observations for 1998.

We calculate the forecast error as the actual earnings minus the median analysts' forecast (Lim, 2001). Next, we define the earnings innovation as the forecast error scaled by the stock price from the pre-announcement day. Thus, both stock returns and the earnings innovations are measured in a common scale- US dollars per dollar of investment. Following Lim (2001) we exclude all observations for which the stock price from the pre-announcement day was less than 5 US dollars to avoid "blown up" estimates of the earnings innovations. Also, we exclude all observations for which the forecast error is larger (in absolute value) than 10 US dollars, which

[1] As stated in the I/B/E/S glossary "For the US and Canada, earnings reports are culled directly from the newswires, adjusted for comparability with estimates and reported to subscribers via the Intra Day Surprise Report, which is delivered five times each trading day."

are likely to be due to data input errors. Finally, to reduce the potential impact of outliers, we exclude all observations in the 2.5 percent tail of the earnings innovation variable. These sample selection procedures lead us to a final sample of 212,000 observations. Descriptive statistics of the earnings innovation series will be discussed in details in the following section.

A note should be made on the definition of actual earnings. Following Bradshaw and Sloan (2002) and other recent studies we use I/B/E/S reported actual earnings. Bradshaw and Sloan (2002) report stock returns being more closely related to the Street earnings reported by I/B/E/S than to the GAAP earnings reported by Compustat. Similar findings are reported by a more recent study by Collins, Li, and Xie (2005).

6.4 Friday vs Non-Friday Announcements: A Temporal Analysis

In this section we conduct a temporal analysis of the earnings announcements. More specifically, by means of both an informal exploratory analysis and statistical tests we examine whether there exists a substantial difference between the earnings announcements during the different trading days of the week, and if so, whether this difference persists over time. In particular, as this is one of the issues of this study, we focus on the Friday earnings announcements. For the purpose of further analysis we divide our total sample into eight subsamples: 1986-1988, 1989-1991, 1992-1993, 1994-1995, 1996-1997, 1998-1999, 2000-2001, 2002-2003 and 2004-2006.

We start with a simple exploratory analysis of the Friday versus non-Friday earnings announcements. For each subsample we plot a quantile-quantile plot of the Friday versus the non-Friday earnings innovations. Superimposed is the straight line which passes through the first and the third empirical quantiles of both samples. Under the null that both the Friday and the non-Friday innovations come from the same distribution the quantile-quantile plots should be located close to this straight line. However, a visual inspection suggests that there exist severe deviations from the hypothetical linear relationship between the quantiles of both variables. In particular, two important findings should be mentioned. First, the difference between the distribution of the Friday and the non-Friday innovations appears to persist over time, and appears to be substantial over the whole time period examined in our study. Second, the deviations appear to be substantially more severe in the negative part of the earnings innovations domain. This preliminary finding comes in line and also extends previous findings who report that firms tend to report "bad news" on Fridays.

As a formal statistical test for each sub-sample we test the null hypothesis that both Friday and the non-Friday earnings innovations come from the same distribution using the Kolmogorov-Smirnov test. The resulting statistics and the corresponding p-values are reported below the quantile-quantile plots for each sub-period. The results of the Kolmogorov-Smirnov test support our findings based on a visual inspection of the quantile-quantile plots. The null hypothesis of both the Friday and the non-Friday earnings innovations coming from the same distribution is strongly rejected for all sub-periods. Interestingly, the difference between the distributions of the Friday and the non-Friday earnings innovations appears to be more pronounced in the 90-s and somewhat more moderate, though still substantial, after the year 2000, at least based on a visual inspection of the quantile-quantile plots.

The difference between the distributions of the Friday and the non-Friday detected by the Kolmogorov-Smirnov test can be due to differences in the mean, the variance, as well as higher moments. In particular, the deviations of the quantile-quantile plot from a straight line suggest that higher moments may also play a substantial role in the dispersion of the distributions. However, since the majority of the existing studies suggests that firms tend to report "bad news" on Fridays, we proceed with the analysis of the *location* of the Friday and the non-Friday distributions. More specifically, we compare two location measures: mean earnings innovation and the proportion of the "bad news" for each trading day. Following previous studies, we define the earnings announcement as "bad news" if the earnings innovations of that particular announcement was negative.

The results are presented in Table 1. For each sub-period and for each trading day we estimate the mean earnings innovation, μ, and the proportion of "bad news", π. For each sub-period the following hypotheses are tested

$$H_0 : \mu_{Monday} = ... = \mu_{Friday},$$

$$H_0 : \pi_{Monday} = ... = \pi_{Friday}.$$

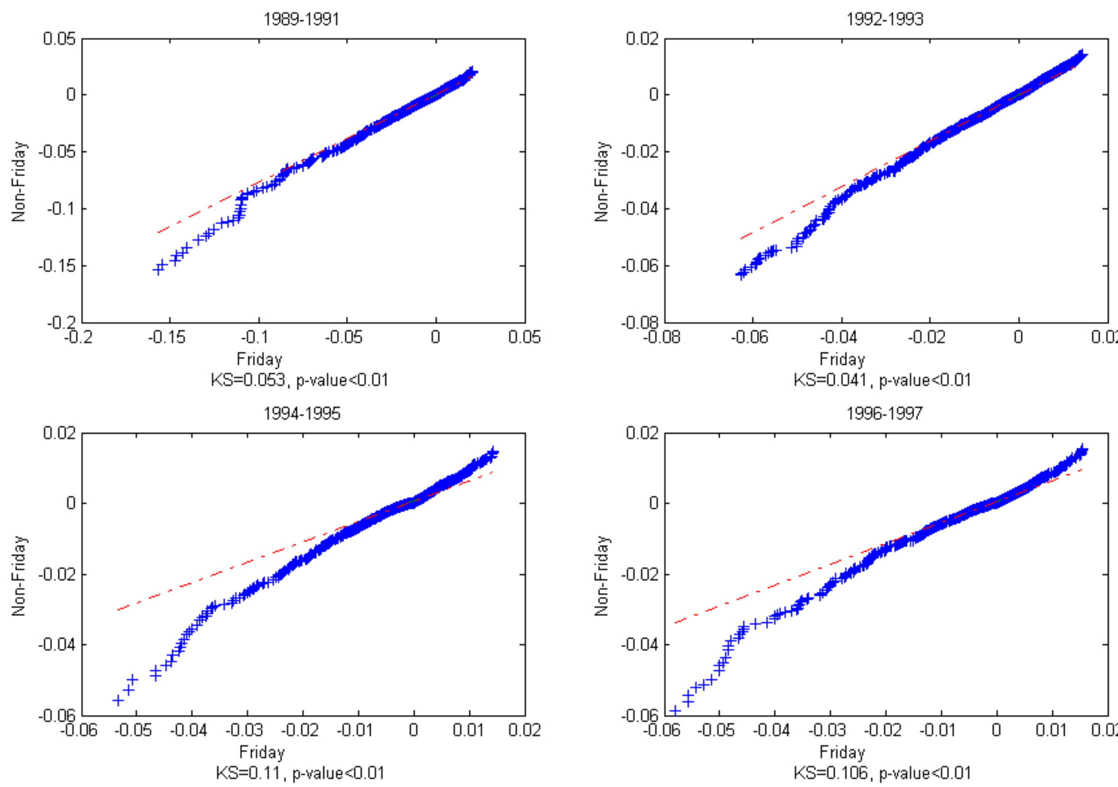

Figure 6-1: QQ plots of the Friday vs non-Friday earnings innovations. KS and p-value are the statistic and the p-value of the two-sample Kolmogorov-Smirnov test.

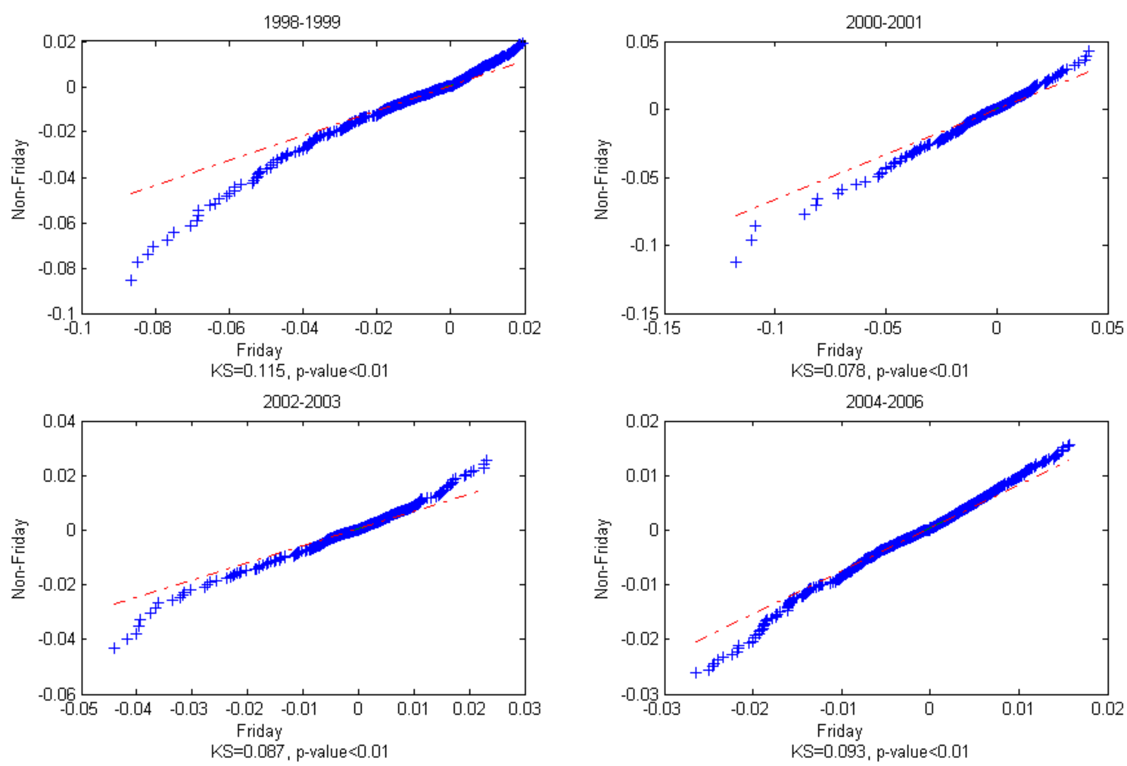

Figure 6-2: QQ plots of the Friday vs non-Friday earnings innovations (*continued*). KS and p-value are the statistic and the p-value of the two-sample Kolmogorov-Smirnov test.

In Table 1 we report the resulting p-values of the Wald test for each of these hypotheses, respectively.

Table 1: Tests of the measures of location by day of the week

	1989-1991		1992-1993		1994-1995		1996-1997	
Day	μ	π	μ	π	μ	π	μ	π
Monday	-0.27**	0.437	-0.118**	0.364	-0.096**	0.348	-0.067**	0.299
Tuesday	-0.289**	0.455	-0.09**	0.363	-0.083**	0.338	-0.061**	0.293
Wednesday	-0.292**	0.442	-0.124**	0.383	-0.095**	0.351	-0.066**	0.308
Thursday	-0.298**	0.465	-0.14**	0.388	-0.091**	0.355	-0.076**	0.314
Friday	-0.377**	0.486	-0.146**	0.405	-0.182**	0.452	-0.145**	0.407
p-value	0.004	0.000	0.002	0.000	0.000	0.000	0.000	0.000
	1998-1999		2000-2001		2002-2003		2004-2006	
	μ	π	μ	π	μ	π	μ	π
Monday	-0.109**	0.295	-0.072**	0.292	0.022**	0.245	-0.0005	0.329
Tuesday	-0.074**	0.274	-0.035**	0.262	0.023**	0.234	0.028**	0.295
Wednesday	-0.094**	0.289	-0.043**	0.284	0.027**	0.241	0.035**	0.275
Thursday	-0.085**	0.284	-0.065**	0.295	0.039**	0.244	0.025**	0.292
Friday	-0.22**	0.396	-0.106**	0.351	-0.017	0.328	-0.019**	0.386
p-value	0.000	0.000	0.023	0.000	0.006	0.000	0.000	0.000

In this table we present the estimates of the mean earnings surprise μ and the proportion of the negative earnings surprises π by the day of the week
The following null hypotheses are tested : H_0: $\mu_{Monday}= ... = \mu_{Friday}$ and H_0: $\mu_{Monday}= ... = \mu_{Friday}$. The p-values of the corresponding Wald statistics are reported below. $^{*(**)}$ denotes 10(5)% significance

Starting with the analysis of the mean earnings innovation estimates, μ's, our findings suggest that during the whole period of the 90-s the mean earnings surprise was significantly negative, a finding which holds for all trading days of the week. This finding is consistent with the results of previous studies, in particular, with the results of Fried and Givoly (1982) and O'Brien (1988), and more recent evidence reported by Lim (2001), and suggests that during the 1990-s on average analysts tended to submit overoptimistic forecasts. Lim (2001) attributes this to a "bias-variance trade-off," where the analysts submit overoptimistic forecasts, which are preferable by the firms' management in order to improve management access and to gain more information in order to reduce the variance of the forecast errors. However, the magnitude of this "overoptimistic" tendency seems to decline gradually, with the estimates of μ becoming smaller in absolute values. Moreover, after the year 2001 there is a shift in the sign of μ becoming significantly positive. This finding is consistent with results by Brown (2001) who also reports a sign reversion in the mean earnings surprise around the end of the 90-s.[2]. Visual inspection of the estimated proportion of the "bad news" π supports the results reported by Brown (2001) that over time there has been a shift in the location of the distribution of the earnings innovations. The estimates of π are almost monotonously declining over the whole time period examined in our study, a decline which is pronounced for all trading days of the week.

Next, we turn to the main issue of this section, namely, the day-of-the-week comparison between the measures of location. For each subperiod we test the two hypotheses, as discussed above. The first hypothesis states that the mean earnings innovation is the same across all trading days of the week, while the second one states the same for the proportion of the "bad news". The resulting p-values of the Wald statistics are reported for each sub-period separately in the columns with headings μ and π, respectively. Our results strongly suggest the presence of a "day-of-the week" effect in both measures of location. Starting with the analysis of the estimates of μ, for all sub-periods the mean of the earnings innovations reported on Friday appears to be substantially lower than during the rest of trading days. This result holds both during the periods before and after the sign reversion in the mean earnings innovation has occurred. Even during the last two periods when for the rest of the days the mean was significantly positive, the estimate of the mean earnings innovation is still negative. A formal Wald test for the equality of the means indicates that the null hypothesis is rejected at any reasonable significance level, suggesting that the "day-of-the week" effect in the earnings innovations is also statistically significant.

[2] Brown (2001) uses a measure of the market earnings expectations which is different from our, the fact which suggests the robustness of his findings. This may also explain a small discrepancy between his and our results regarding the year when the sign reversion has occurred.

The analysis of the estimated proportion of the "bad news" yields similar results. For all sub-periods the estimates of π are significantly larger for the Friday trading session. Though the difference between the Friday and the non-Friday estimates of π seems to decline during the last two periods, compared to the one during the 90-s, it still remains quite substantial. This finding is supported by the Wald test, which suggests that the null of equal "bad news" proportion should be rejected.

It is possible that the "day-of the-week" effect is not only due to Friday announcements, but also due to difference between the distributions of the earnings innovations on other trading days. To check this conjecture, we repeat our analysis, but by excluding the Friday announcements from our analysis. That is, we test the equality of μ-s and π-s for the Monday to Thursday announcements. In contrast to our previous findings, our results suggest that, generally, the null of equal location measures for Monday-Thursday trading sessions cannot be rejected. The null of equal mean is rejected only for the last sub-period, while the null of equal "bad news" proportion is rejected for the fourth, sixth, and the last sub-periods [3]. Moreover, no consistent pattern in the differences between the estimates of either μ or π for the Monday-Thursday trading sessions can be detected. These results suggest that the lion's share of the "day-of-the week" effect in the earnings announcements is due to the difference between the distributions of the Friday and the non-Friday earnings innovations.

Overall, our findings support the results of the previous studies, such as Damodaran (1989), that suggest that firms tend to report "bad news" on Fridays. More importantly for the context of this paper, our findings suggest that this announcement strategy has been persistent for the last two decades. Then the natural question that arises whether stock market investors learned about this strategy. In particular, if investors have detected the tendency of firms to report "bad news" on Friday, then we would expect to see a gradual increase in the magnitude of a reaction by investors to Friday news, which will be reflected in a gradual change in the earnings response function. This will be the issue of the following section.

[3] The results are available upon request from the author.

6.5 Friday vs Non-Friday Earnings Response Function: A Temporal Analysis

In this section we study the evolution over time of the earnings response function of the firms listed on the US markets over the period 1989-2006. This section consists of two parts. In subsection 6.5.1 we describe the methodology we use to compare the response of stocks to earnings innovations due to Friday versus non-Friday announcements. Next, we present and discuss our findings in subsection 6.5.2.

6.5.1 Methodology

Nonparametric Analysis

The purpose of this section is to study the evolution over time of the earnings response function, that is, the function that links the expected stock returns to the earnings innovations. Moreover, our goal is to conduct statistical tests on the difference between the earnings response functions for the Friday versus the non-Friday trading sessions. Clearly, a correct specification of the earning response function plays a crucial role in our analysis. To set forth notations, let $r_{i,t}$ denote the excess return on the stock of the firm i at the day of the earnings announcement for the period t, which we measure as the return on the stock minus the return on the equalyy weighted market portfolio. Also, let $UE_{i,t}$ denote the unexpected earning (earnings innovation) of the firm i for the period t. We measure $UE_{i,t}$ as the difference between actual earning and the consensus forecast scaled by a stock price from the last trading day before the announcement. Furthermore, let the subscripts *fr* and *nfr* denote "Friday" and "non-Friday", respectively. Then, the following model is considered

$$r_{i,t} = F\left(UE_{i,t}, I_{fr,i,t}\right) + \epsilon_{i,t}$$

$$E(\epsilon_{i,t}|UE_{i,t}, I_{fr,i,t}) = 0$$

Here $I_{fr,i,t}$ is the indicator function which takes the value 1 if the announcement has been during a Friday trading session and 0 otherwise, $F(\cdot,\cdot)$ is the earnings response function, and $\epsilon_{i,t}$ is the noise which is assumed to have zero mean conditional upon the earnings innovation and the Friday dummy variable. Then the question of whether investors respond differently to Friday versus non Friday announcements can be transformed into testing the following null hypothesis

$$H_0 : F(\cdot, 1) = F(\cdot, 0)$$

To gain a first impression on the returns-earnings relationship and its evolution over time we begin with a nonparametric exploratory analysis. For each sub-period we separately estimate the earnings response function for the Friday and the non-Friday earnings announcements as follows

$$\hat{F}(UE, 1) = \frac{\sum_{t=1}^{T} \sum_{i=1}^{n} r_{i,t} K(\frac{UE - UE_{i,t}}{h}) I_{fr,i,t}}{\sum_{t=1}^{T} \sum_{i=1}^{n} K(\frac{UE - UE_{i,t}}{h}) I_{fr,i,t}}$$

$$\hat{F}(UE, 0) = \frac{\sum_{t=1}^{T} \sum_{i=1}^{n} r_{i,t} K(\frac{UE - UE_{i,t}}{h})(1 - I_{fr,i,t})}{\sum_{t=1}^{T} \sum_{i=1}^{n} K(\frac{UE - UE_{i,t}}{h})(1 - I_{fr,i,t})}$$

where $K(\cdot)$ is a kernel function and h denotes the bandwidth. Throughout this study we shall use a Gaussian kernel, while the choice of bandwidth will be based on Silverman's "rule of thumb" (Silverman, 1986). Under mild conditions $\hat{F}(\cdot, 1)$ and $\hat{F}(\cdot, 0)$ are (pointwise) consistent estimators of the true earnings response functions $F(\cdot, 1)$ and $F(\cdot, 0)$, respectively. Moreover, our large sample size allows us to estimate $F(\cdot, 1)$ and $F(\cdot, 0)$ with a reasonable degree of accuracy. Thus, we may draw our first, though informal, conclusions on the existence of a "Friday effect" by comparing the kernel estimates of $F(\cdot, 1)$ and $F(\cdot, 0)$.

Next, we turn to the formal nonparametric test. We use a test proposed by Yatchew (2003). Let us assume that the first derivatives of both $F(\cdot, 1)$ and $F(\cdot, 0)$ are bounded and the error terms $\epsilon_{i,t}$ are homoscedastic with variance σ_ϵ^2. This specification is still fairly general in sense that we do not impose any other restrictions on the functional form of neither $F(\cdot, 1)$ nor $F(\cdot, 0)$.

Let us divide our sample into two samples, where the sample A includes all earnings announcements made on Friday while the sample B includes all the non-Friday announcements. Next, within each sample let us reorder the data so that the earnings innovations $UE_{i,t}$'s are in increasing order. The following consistent "within" estimators of the variance are considered[4]

$$s_A^2 = \frac{1}{2n_A}\sum_{i=2}^{n_A}(r_{A,i} - r_{A,i-1})^2$$

$$s_B^2 = \frac{1}{2n_B}\sum_{i=2}^{n_B}(r_{B,i} - r_{B,i-1})^2$$

Next, let us pool all the data an reorder so that the pooled $UE_{i,t}$'s are in increasing order and define the pooled estimator of the variance

$$s_P^2 = \frac{1}{2(n_A + n_B)}\sum_{i=2}^{n_A+n_B}(r_i - r_{i-1})^2$$

Our testing procedure is based on the following statistic

$$\Upsilon = (n_A + n_B)^{1/2}(s_P^2 - \frac{n_A}{n_A + n_B}s_A^2 - \frac{n_B}{n_A + n_B}s_B^2)$$

If $F(\cdot, 1) = F(\cdot, 0)$ then both within and pooled estimators are consistent and should yield similar estimates. On the other hand, if the null hypothesis does not hold, the "within" estimators are still consistent, while the pooled estimator overestimates the variance. Furthermore, it can be shown that under the null the limiting distribution of this statistic is normal with zero mean and the variance being equal to $2\pi^*\sigma_\epsilon^4$ where π^* is the probability that consecutive observations in the pooled reordered data set come from different populations. Consistent estimators of π can be easily obtained (see Yatchew, 2003 for further details).

The test proposed by Yatchew (2003) has a number of important advantages. First, being nonparametric, we do not impose any assumptions regarding the functional form of the earnings response function. This virtue makes this test more robust compared to standard parametric tests, where a particular form of the earnings response function has to be assumed. Also, since the rate of convergence of Yatchew's statistic is the same as parametric tests it is likely to be more powerfull against the alternatives than other nonparametric tests. On the other hand, while testing whether two functions $F(\cdot, 1)$ and $F(\cdot, 0)$ are different, the test does not allow

[4] For the proof of consistency of the differencing variance estimators a reader is reffered to Yatchew (2003).

us to compare the magnitude and the direction of this difference. That is, from this test we are not able to test whether the stock returns are more or less sensitive to the Friday earnings announcements than during the rest of trading days. Moreover, it does not allow us to analyze how the difference between $F(\cdot, 1)$ and $F(\cdot, 0)$ (if detected) has evolved over time. Therefore, in addition to nonparametric test of Yatchew (2003) we also proceed with a parametric analysis.

Parametric Analysis

We assume that the relationship between the excess stock returns and the earnings innovations can be described by the following regression model

$$r_{i,t} = \alpha + F\left(UE_{i,t}, I_{fr,i,t}\right) + \epsilon_{i,t}$$

$$E(\epsilon_{i,t}|UE_{i,t}, I_{fr,i,t}) = 0$$

$$F(UE_{i,t}, 1) = \beta^{+}_{fr} \arctan\left(\gamma^{+} UE_{i,t}\right) I^{+} + \beta^{-}_{fr} \arctan\left(\gamma^{-} UE_{i,t}\right) I^{-}$$

$$F(UE_{i,t}, 0) = \beta^{+}_{nfr} \arctan\left(\gamma^{+} UE_{i,t}\right) I^{+} + \beta^{-}_{nfr} \arctan\left(\gamma^{-} UE_{i,t}\right) I^{-}$$

Here, $I^{+}(I^{-})$ is the indicator function which takes the value 1 if the earnings announcement is nonnegative (negative). Also, I_{fr} is the indicator function which takes the value 1 (0) if the announcement has been made during a Friday (non-Friday) trading session as discussed before, and α, β's and γ's are the parameters to be estimated. This model is an extended version of the S-shape earnings response function proposed by Freeman and Tse (1992). They show that this model is superior compared to a standard linear earnings-returns models and that it can accommodate varying degrees of non-linearity, from approximately linear to highly nonlinear.

Two important differences between the original model and the one we use in this paper should be mentioned. First, we introduce an additional degree of freedom to the original model of Freeman and Tse (1992) by allowing the relation between stock returns and earnings innovations to be dependent on whether "good" or "bad" news is released. Some evidence that security returns have a different degree of sensitivity to positive and negative earnings innovations has been reported by a number of the previous studies (see, for instance, Abdel-khalik, 1990). The distinction between positive and negative earnings innovations is particularly important in the context of this study, since Friday earnings announcements are characterized by a substantially higher proportion of "bad" news, as we have already discussed above. Second, as this is one of the two main issues studied in this paper, we allow the earnings response function to differ between Friday and Non-Friday announcements via β^+_{fr} versus β^+_{nfr}, and β^-_{fr} versus β^-_{nfr}. Thus, we shall examine the question of whether there exists a "Friday effect" in the earnings response function by separately testing the following hypotheses

$$H_0 : \beta^+_{fr} = \beta^+_{nfr}$$

$$H_0 : \beta^-_{fr} = \beta^-_{nfr}$$

via standard Wald tests.

6.5.2 Empirical Results

Nonparametric Analysis

We start with the nonparametric exploratory analysis as described in subsection 6.5.1. For each sub-period we separately estimate the earnings response function for the Friday and the non-Friday earnings announcements by using the kernel smoothing method. Both functions are estimated over the range of $(q_{UE,0.025}, q_{UE,0.975})$ with $q_{UE,0.025}$ and $q_{UE,0.975}$ denoting 2.5% and 97.5% sample quantiles, respectively.

The estimates are depicted in Figures 6.3 and 6.4. Visual inspection of the earnings response functions suggests that the earnings-return relationship is highly nonlinear. More specifically, the estimated earnings response functions exhibit more or less the S-shape pattern, with stock returns being more sensitive to earnings surprises in the moderate (around zero) region, while turning almost flat for large earnings innovations. These findings support the results of Freeman and Tse (1992), and Das and Lev (1994), who report a similar pattern of the earnings-returns relationship. Moreover, our results suggest that the S-shape pattern is persistent over the last two decades. This finding complements the results of Freeman and Tse (1992), suggesting that their results are not driven by sample selection, and also justifies the choice of our parametric model, described in subsection 6.5.1.

A comparison of the Friday versus the non-Friday estimates of the earnings response functions yields particularly intriguing results. It appears that during the years 1989-1997 the stock prices were more sensitive to the earnings announcements released during the non-Friday trading sessions, compared to those released on Fridays, with the estimate of the non-Friday earnings response function being substantially "steeper". Interestingly, the "Friday effect" appears to be more pronounced for the positive earnings innovations, or, in other word, when "good news" is released. On the other hand, no substantial difference between the Friday and the non-Friday estimates is observed for the negative earnings surprises for the first four periods. Moreover, while being especially pronounced for the first two sub-periods, the magnitude of the "Friday effect" seems to decay gradually, until 1996-1997 where both estimates almost coincide. Further, it seems that there has been a reversal in the "Friday effect" by the end of 90-s. More specifically, starting from the year 1998 the stock returns appear to be *more* sensitive to the earnings announcements released during Friday trading sessions compared to those released during non-Friday trading days. Interestingly, for the last four sub-periods, that is, for the period between 1998-2006, the difference appears to be more pronounced for the negative earnings innovations. These preliminary findings suggest that there has been a structural shift in the "Friday effect", which can be potentially attributed to stock market investors learning the tendency of firms to release "bad news" on Friday.

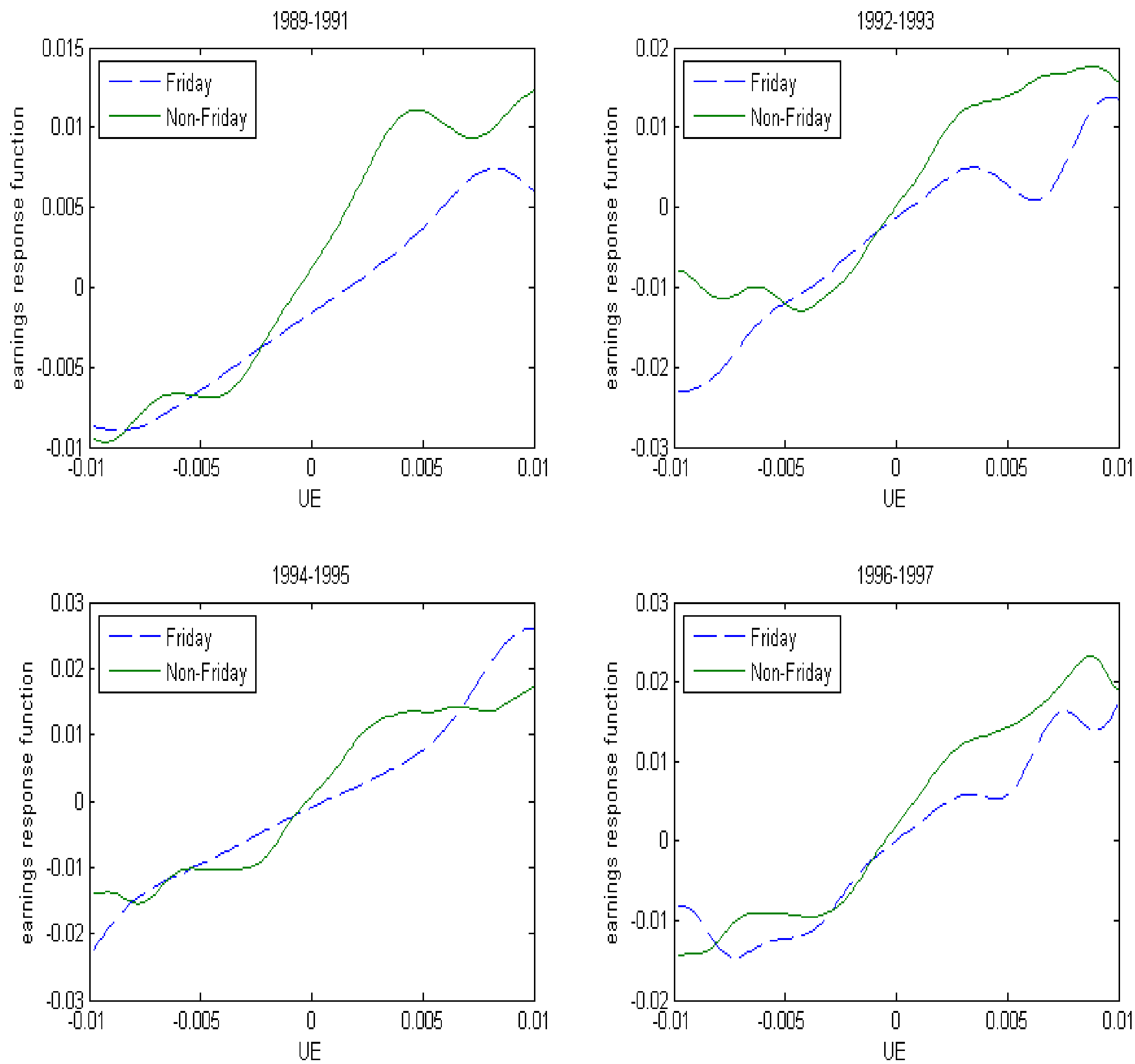

Figure 6-3: Kernel estimates of the earnings response function. Dashed line-Friday announcements, solid line-non-Friday announcements.

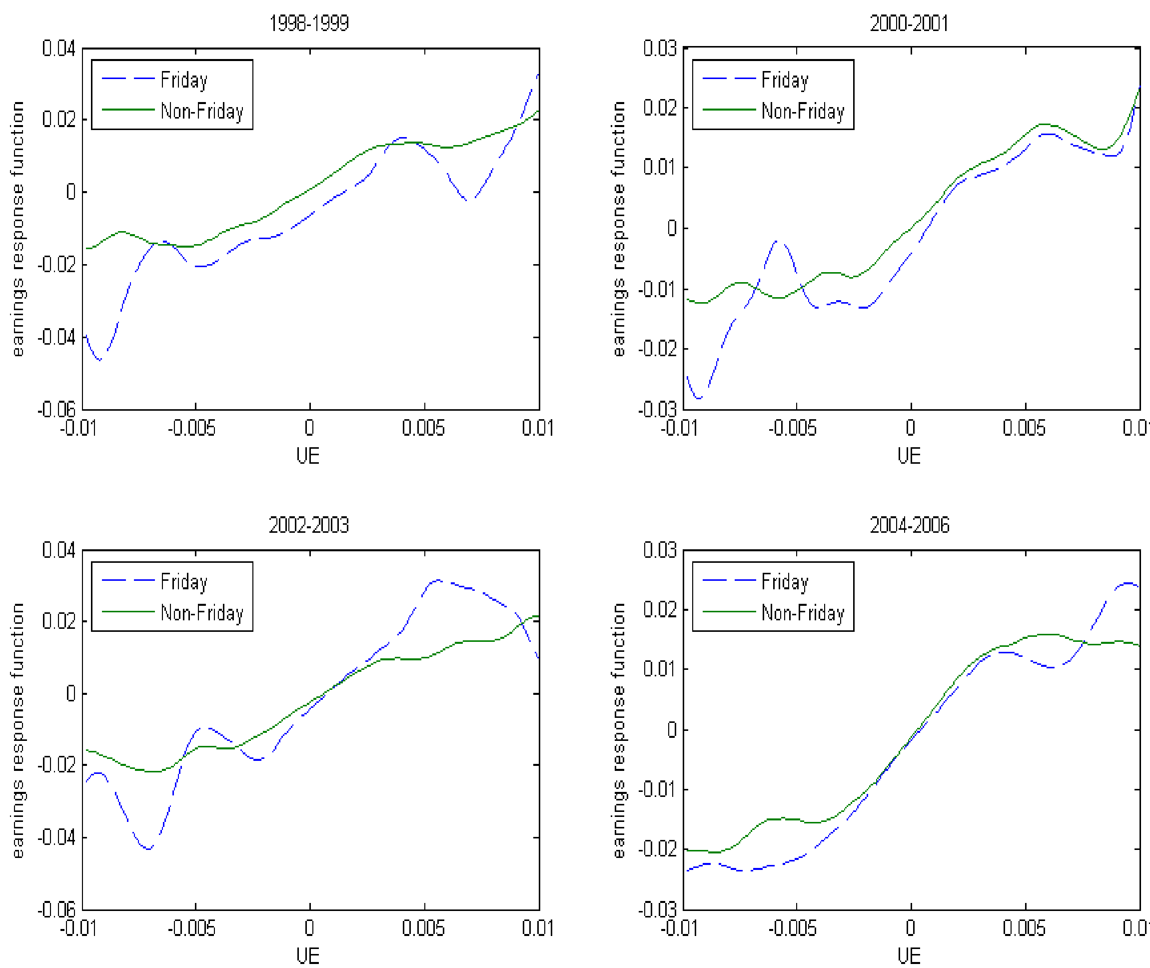

Figure 6-4: Kernel estimates of the earnings response function (*continued*). Dashed line-Friday announcements, solid line-non-Friday announcements.

	1989-1991		1992-1993		1994-1995		1996-1997	
	σ^2_ϵ	N.obs	σ^2_ϵ	N.obs	σ^2_ϵ	N.obs	σ^2_ϵ	N.obs
Friday	0.00141	3953	0.00185	5485	0.0021	2250	0.00243	2516
Non-Friday	0.00137	16605	0.00178	14297	0.00174	23145	0.00207	29218
Pooled	0.00136	20558	0.00179	19782	0.00177	25395	0.0021	31374
$\widetilde{\Upsilon}$	-2.05**		-3.41**		-2.99**		1.57	
	1998-1999		2000-2001		2002-2003		2004-2006	
	σ^2_ϵ	N.obs	σ^2_ϵ	N.obs	σ^2_ϵ	N.obs	σ^2_ϵ	N.obs
Friday	0.00361	2230	0.00384	1676	0.00328	1338	0.00233	2139
Non-Friday	0.00326	28204	0.00373	23046	0.00241	21660	0.00186	34238
Pooled	0.0032	30434	0.0038	24722	0.00246	22998	0.00192	36377
$\widetilde{\Upsilon}$	-10.86**		-2.37**		-2.77**		6.39**	

Table 2: Yatchew (2003) difference-of-variance tests

*(**) denotes 10(5)% significance

Next, we proceed with formal tests of the "Friday effect". We start with the results of the Yatchew (2003) nonparametric test. First, a visual inspection of both the "within" and the pooled variance estimates suggests that at the announcement date the stock returns are characterized by an unusually high variance. For instance, if we consider the pooled variance estimate from the 1989-1991 period, it translates into a 35 percent variance or about 60 percent standard deviation in annual terms. These estimates are becoming even larger and reach their maximum during the 2000-2001 period, which can be due to the collapse of the "dot.com" bubble, as well as the series of corporate scandals which took place by the end of 2001. These findings are consistent with other studies which report the abnormal stock return volatility around the earnings announcement days (see Ball and Kothari, 1991, Landsman and Maydew, 2002, and Collins, Zi and Xie, 2005, among others). Moreover, it appears that the stock return volatility at the announcement day has increased over the last two decades. This observation supports the results reported by Ladsman and Maydew (2002). Also, note that these are the estimates of the *conditional* variance. In other words, the increase in the estimated stock variance that we observe can be attributed neither to an increase in the variance of the unexpected earnings nor to a stronger earnings-returns relation, a finding which supports the results of Francis, Schipper, and Vincent (2002), who attribute this increase to an over-time expansion in the amount of concurrent information disclosed in earnings response press releases.

Next, we turn to the evaluation of the results of the Yatchew (2003) test with the test statistic denoted by $\widetilde{\Upsilon}$, whose asymptotic distribution should be standard normal under the null of no "Friday effect" in the earnings response function. Recall that if the earnings response functions during Friday and non-Friday trading days are the same, then we would expect both "within" and pooled variance estimates to be similar, which would cause $\widetilde{\Upsilon}$ to be small. However, our results suggest that this is clearly not the case. The test statistic $\widetilde{\Upsilon}$ is highly statistically significant for all but one sub-period. The only exception is 1996-1997, where $\widetilde{\Upsilon}$ is marginally significant with a p-value being equal to 0.11. Overall, based on the results of this test, two conclusion can be drawn. First, we find strong evidence for a "Friday effect" in the earnings response function, supporting the results of previous studies, such as Della Vigna and Pollet (2005). Noteworthy, in contrast to these studies we conducted our test in a nonparametric framework, which suggests that our findings are robust to different assumptions regarding the functional form of the earnings-returns relation. Second, and more importantly, we find that the difference between the response of stock returns to Friday versus non-Friday announcements is persistent over time. However, based on the results of this test we still are not able to draw conclusions regarding either the magnitude or the evolution over time of this difference. In addition, since Friday announcements are characterized by a significantly larger proportion of "bad news", for a further analysis of the "Friday effect" it is important to dichotomize the earnings announcements into positive and negative earnings surprises. Therefore, to gain further insight into the mechanism and the dynamics of the "Friday effect", we now turn to a parametric analysis.

Parametric Analysis

It is straightforward to verify that the marginal impact of an increase in the earnings innovation on the expected excess return implied by this model equals

$$\frac{\beta_{fr}^{+}\gamma^{+}}{(1+\gamma^{+2}UE_{i,t}^{2})} \text{ for a Friday earnings innovations}$$

$$\frac{\beta^{+}_{nfr}\gamma^{+}}{(1+\gamma^{+2}UE^{2}_{i,t})} \text{ for a non-Friday earnings innovations}$$

when the earnings surprise is positive and

$$\frac{\beta^{-}_{fr}\gamma^{-}}{(1+\gamma^{-2}UE^{2}_{i,t})} \text{ for a Friday earnings innovations}$$

$$\frac{\beta^{-}_{nfr}\gamma^{-}}{(1+\gamma^{-2}UE^{2}_{i,t})} \text{ for a non-Friday earnings innovations}$$

when the earnings surprise is negative. Thus, the analysis of the magnitude of the "Friday effect," as well as its evolution over time, can be conducted by estimating the ratios β^{+}_{fr} to β^{+}_{nfr}, and β^{-}_{fr} to β^{-}_{nfr}.

In Table 3 we present the estimation results of the extended Freeman-Tse (1992) model, described in the previous subsection. The model was estimated for each sub-period covered in our study using the Gauss-Newton algorithm, following related studies (Freeman and Tse, 1992, Harvey and Beneish, 1998). To examine the numerical stability of our results, we estimate our model with twenty randomly chosen vectors of starting values and compare the estimates. Our results suggest that the estimates are numerically stable with respect to different starting values.

We start with a simple visual inspection of the estimated parameters. The large values of the estimates of γ suggest that the relation between the excess returns and the earnings' innovations is highly non-linear, a finding which supports the results of Freeman and Tse (1992). This holds both for negative and positive earnings' innovations and for all the sub-periods covered in our study, a finding which suggests that the non-linearity in the returns-earnings relationship is substantial and also persistent over time. A visual inspection of the estimates of β reveals that these estimates are gradually increasing over time, in contrast to the estimates of γ', where no such tendency can be detected. This finding suggests that over time the earnings information is reflected more rapidly in stock prices, resulting in the US markets becoming more informationally efficient.

Next, we turn to a formal comparison of the Friday versus non-Friday earnings response functions. As already discussed above, in the extended Freeman-Tse (1992) model the "Friday effect" in the earnings response function is captured by the deviations of the $\beta^{+}_{fr}/\beta^{+}_{nfr}$ and $\beta^{-}_{fr}/\beta^{-}_{nfr}$ ratios from unity. The $\beta^{+}_{fr}/\beta^{+}_{nfr}$ ratio measures the "Friday effect" for positive earnings innovations, while the $\beta^{-}_{fr}/\beta^{-}_{nfr}$ ratio measures the difference between the Friday and the non-Friday earnings' response functions for the negative earnings' surprises.

Ratios lower than one indicate that the stock prices' response to the earnings surprises is weaker during a Friday than during a non-Friday trading session, and vice versa. We report these ratios as well as whether the latter are significantly different from one for each sub-period examined in our study.

Starting with the analysis of the $\beta^{+}_{fr}/\beta^{+}_{nfr}$ ratio our findings indicate that for the 90-s the earnings response function was characterized by a substantial "Friday effect" in the positive part of the earnings' innovations domain. The "Friday effect" is particularly strong during the first two sub-periods, that is, during the beginning of the 1990-s, with the estimated ratios less than 0.5. In other words, during these periods the response of the stock prices to the positive earnings surprises on Fridays was more than twice weaker than the one during the non-Friday sessions. Interestingly, the estimated $\beta^{+}_{fr}/\beta^{+}_{nfr}$ ratios tend to increase over time, though the increase is not monotonous. More specifically, while during the 1990-s the ratio was significantly smaller than one, it becomes larger than one during the last two periods with the deviation from unity being also statistically significant for the 2001-2003 period. This finding provides some preliminary evidence that stock market investors learn over time the strategic information releases of firms.

Table 3: Freeman-Tse (1992) extended model

Coeff.	1989-1991	1992-1993	1994-1995	1996-1997
μ	-0.0009^{*} (0.0005)	-0.001^{*} (0.0006)	-0.0006 (0.0005)	-0.0004 (0.0005)
β^{+}_{fr}	0.0038^{**} (0.0008)	0.0052^{**} (0.001)	0.0096^{**} (0.0016)	0.0074^{**} (0.0015)
β^{+}_{nfr}	0.0078^{**} (0.0006)	0.011^{**} (0.001)	0.011^{**} (0.0008)	0.011^{**} (0.0007)
β^{-}_{fr}	0.0071^{**} (0.0012)	0.0097^{**} (0.0013)	0.011^{**} (0.0017)	0.011^{**} (0.0019)
β^{-}_{nfr}	0.0069^{**} (0.0008)	0.0091^{**} (0.001)	0.0092^{**} (0.0008)	0.0081^{**} (0.0008)
γ^{+}	2366.7^{**} (563.2)	992.1^{**} (222.4)	984.6^{**} (178.95)	1547.8^{**} (264.6)
γ^{-}	391.1^{**} (123.8)	777.1^{**} (216.1)	862.1^{**} (215.15)	943.6^{**} (270.1)
$\beta^{+}_{fr}/\beta^{+}_{nfr}$	0.49^{**}	0.46^{**}	0.86	0.7^{**}
$\beta^{-}_{fr}/\beta^{-}_{nfr}$	1.03	1.08	1.19	1.36
Adj. R^2	0.034	0.039	0.044	0.034
No.obs	20588	19782	25395	31374
	1998-1999	2000-2001	2002-2003	2004-2006
μ	-0.0027^{**} (0.0006)	-0.0022^{**} (0.0007)	-0.005^{**} (0.0006)	-0.0039^{**} (0.0005)
β^{+}_{fr}	0.0081^{**} (0.0017)	0.011^{**} (0.0022)	0.018^{**} (0.0024)	0.015^{**} (0.0015)
β^{+}_{nfr}	0.012^{**} (0.0008)	0.013^{**} (0.0011)	0.013^{**} (0.0008)	0.014^{**} (0.0006)
β^{-}_{fr}	0.015^{**} (0.0029)	0.014^{**} (0.0036)	0.013^{**} (0.003)	0.014^{**} (0.0023)
β^{-}_{nfr}	0.0095^{**} (0.0011)	0.0073^{**} (0.0013)	0.0078^{**} (0.0012)	0.0095^{**} (0.0008)
γ^{+}	1580.3^{**} (282.3)	853.1^{**} (183.7)	957.4^{**} (163,13)	950.6^{**} (115.42)
γ^{-}	433.3^{**} (137.3)	578.1^{**} (256.9)	956.3^{**} (372.01)	688.9^{**} (156.5)
$\beta^{+}_{fr}/\beta^{+}_{nfr}$	0.65^{**}	0.81	1.41^{**}	1.05
$\beta^{-}_{fr}/\beta^{-}_{nfr}$	1.55^{*}	1.87^{*}	1.72^{*}	1.43^{*}
Adj. R^2	0.029	0.022	0.037	0.055
No.obs	30434	24722	22998	36377

$^{*(**)}$ denotes 10(5)% significance

White heteroskedasticity-consistent standard errors in parentheses

The analysis of the estimates of $\beta^-_{fr}/\beta^-_{nfr}$ yields particularly intriguing results. Already from the beginning of the 90-s the estimated ratio is greater than one, though for the first sub-periods the difference is not statistically significant. Thus, for all the periods examined in our study the response of the stock prices to the negative earnings surprises appears to be *stronger* during Fridays than during non-Friday trading days. Moreover, this difference becomes statistically significant, starting from 1998. Also, the magnitude of the "Friday effect" is almost monotonously increasing over time. While during the 1989-1991 period the "Friday effect" could be considered as negligible, with the estimated earnings response ratio being equal to 1.03, it becomes economically significant by the end of 90-s with the average estimated earnings response ratio of about 1.6 for the last four sub-periods. In other words, during the last eight years the response of the stock prices to the negative earnings' surprises was on average stronger by 60% during Friday than during non-Friday trading days. These findings suggest that over time the investors learned the firms' strategy of releasing "bad news" on Fridays and started following the Friday information releases more carefully. Moreover, it appears that during the last periods the investors tend to overreact to "bad news" announcements released on Fridays compared to "bad news" released during the non-Friday trading sessions. It is likely that the investors tend to interpret the losses reported on Fridays as those that the firms particularly would like to hide from the pubic, and, thus, investors will treat these announcements as particularly important ones.

To gain some further insight into the dynamics of the "Friday effect," we estimate the extended Freeman-Tse (1992) model year-by-year. This way we obtain 18 estimates of the earnings response ratio, both for the positive and the negative earnings innovations. We plot these estimates in Figure 3, where the dashed line depicts the estimates of the $\beta^+_{fr}/\beta^+_{nfr}$ ratios, and the solid line denotes the time path of the estimates of $\beta^-_{fr}/\beta^-_{nfr}$ ratios. The time path of the earnings response ratios will serve as a crude proxy for the investors' "learning curve" of the "Friday effect". A visual inspection of the ratios suggests that both are increasing over time. Formal tests suggest that this trend is both economically and statistically significant. A simple linear regression with a time trend explains about 26% of the total variance of the estimated $\beta^-_{fr}/\beta^-_{nfr}$ ratios (slope=0.0474 with p- value=0.04, $R^2 = 0.26$). The results for the $\beta^+_{fr}/\beta^+_{nfr}$ ratios are even more impressive, where the same regression explains more than

50% of the $\beta^{+}_{fr}/\beta^{+}_{nfr}$ ratio's total variance (slope=0.0475 with p-value<0.01, $R^2 = 0.55$). The estimate of the $\beta^{+}_{fr}/\beta^{+}_{nfr}$ ratio was about 0.5 during 1989, or, in other words, the response of stock prices to positive earnings announcements was about twice weaker during Friday sessions compared to non-Friday trading days. This ratio was gradually increasing until it reached the level of 1 by the year 2006, suggesting that during the recent period no "Friday effect" in the earnings response function for the positive earnings innovations is detected. Turning to the estimates of the $\beta^{-}_{fr}/\beta^{-}_{nfr}$ ratio, we find that the latter was about 0.75 during 1989, suggesting that the response of stock prices to negative earnings announcements released on Fridays was substantially weaker than the ones on non-Friday trading days. However, this tendency rapidly reverts and already by the beginning of 90-s we find the earnings response being slightly above the level of 1. Further, the earnings response ratio experienced a sharp increase with a peak of 2.2 during 1999. This is possibly due to the stock market investors concentrating on the firms' losses, following the collapse of the "internet bubble". By the year 2006 the estimated earnings response ratio for the negative earnings innovations was 1.69, suggesting that recently the stock price response to the firms' announced losses is about 70% stronger than the one during the non-Friday trading days. Overall, the analysis of the investors' "learning curve" supports our conclusions, drawn from the extended Freeman-Tse (1992) model, that over time investors learned the firms' announcement strategy of releasing the "bad news" during Friday trading sessions.

"Friday effect" and the Pre-Announcement Uncertainty

The last aspect we study in this paper is the relation between the analysts' forecast uncertainty and the "Friday effect". A substantial body of academic literature reports a positive relationship between the magnitude of the response of the stock prices to the earnings innovations and the level of the informational disclosure (Freeman, 1987; Imhoff and Lobo, 1992; Ng *et al.*, 2006). Understanding the role of the level of the informational disclosure and, in particular, the level of the pre-announcement uncertainty is crucial for a deeper understanding of the nature of the "Friday effect". If the "Friday effect" is caused by the investors' distraction during the Friday trading sessions, then it is likely that its magnitude will vary with the accuracy of the informational disclosure and, in particular, the accuracy of the analysts' forecasts before the

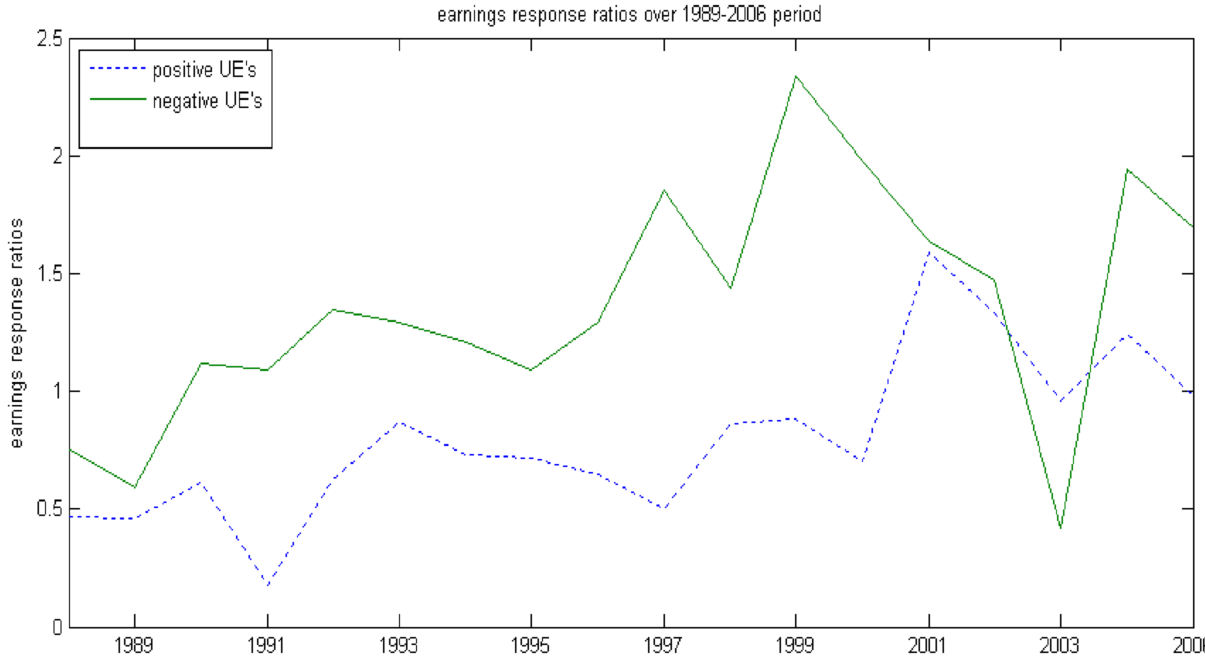

Figure 6-5: Temporal analysis of the "Friday effect" by year. Dashed line denotes earnings response ratios for the positive earnings innovations, solid line depicts earnings response ratios for the negative earnings innovations.

actual earnings announcement is released. More specifically, we would expect the magnitude of the "Friday effect" to be decreasing in the level of the analysts' forecasts inaccuracy.

Following Imhoff and Lobo (1992) we use the standard deviation of the analysts' forecasts as a proxy for the pre-announcement uncertainty. The estimates of the standard deviations of the analysts' forecasts were obtained from the I/B/E/S for each firm-quarter observation included in our sample. To study the impact of the pre-announcement uncertainty on the "Friday effect" the following version of the extended Freeman-Tse (1992) model is estimated

$$r_{i,t} = \alpha + F\left(UE_{i,t}, I_{fr,i,t}, UNC_{i,t}\right) + \epsilon_{i,t}$$

$$E(\epsilon_{i,t}|UE_{i,t}, I_{fr,i,t}, UNC_{i,t}) = 0$$

$$F(UE_{i,t}, 1) = \left\{\beta^{+} + \delta^{+} UNC_{i,t}\right\} \arctan\left(\gamma^{+} UE_{i,t}\right) I^{+} + \left\{\beta^{-} + \delta^{-} UNC_{i,t}\right\} \arctan\left(\gamma^{-} UE_{i,t}\right) I^{-}$$

$$F(UE_{i,t},0) = \phi_{i,t}^{+}\left\{\beta^{+} + \delta^{+}UNC_{i,t}\right\}\arctan(\gamma^{+}UE_{i,t})I^{+} + \phi_{i,t}^{-}\left\{\beta^{-} + \delta^{-}UNC_{i,t}\right\}\arctan(\gamma^{-}UE_{i,t})I^{-}$$

$$\phi_{i,t}^{+} = \phi_0^{+} + \phi_1^{+}UNC_{i,t}$$

$$\phi_{i,t}^{-} = \phi_0^{-} + \phi_1^{-}UNC_{i,t}$$

where the level of the pre-announcement uncertainty, denoted by $UNC_{i,t}$, is measured by the standard deviation of the analysts' forecasts, measured during the last month before the actual announcement has been released. The impact of the pre-announcement uncertainty on the earnings response function comes via two channels. First, we allow pre-announcement uncertainty to affect the earnings-returns link via the parameters δ^{+} and δ^{-}. This controls for a potential relationship between the sensitivity of the stock returns to the earnings innovations and the pre-announcement uncertainty, as reported by Imhoff and Lobo (1992). These parameters link the level of the pre-announcement uncertainty and the "absolute" sensitivity of stock returns to the earnings innovations. Second, we allow the magnitude of the "Friday effect" to be dependent on the level of the pre-announcement uncertainty via the ϕ_1^{+} and ϕ_1^{-} parameters. That is, the earnings response ratio are allowed to vary with the level of the pre-announcement uncertainty. For instance, if ϕ_0^{+} and ϕ_0^{-} are greater than 1 and ϕ_1^{+} and ϕ_1^{-} are negative, then the earnings-returns link is weaker during Fridays than during the rest of the days for the firms with low pre-announcement uncertainty, but this difference decays as the level of the pre-announcement uncertainty is increasing. On the other hand, if both ϕ_0^{+} and ϕ_0^{-} are smaller than 1 and ϕ_1^{+} and ϕ_1^{-} are negative, then the magnitude of the "Friday effect" is increasing with the level of pre-announcement uncertainty.

This further extension of the Freeman-Tse (1992) model nests a number of important models as special cases which can be formulated as follows

$$\text{No "Friday effect"} \quad H_0 : \phi_0^{+} = \phi_0^{-} = 1 \text{ and } \phi_1^{+} = \phi_1^{-} = 0$$

$$\text{Constant "Friday effect"} \quad H_0 : \phi_1^{+} = \phi_1^{-} = 0$$

The first hypothesis simply states that the Friday and the non-Friday earnings response functions coincide. Note that in this case we still allow the earnings response function to be affected by pre-announcement uncertainty via the parameters δ_{fr}^{+} and δ_{fr}^{-}. The second hypothesis allows for a "Friday effect" which does not depend on the level of pre-announcement uncertainty. Note that this scenario yields constant earnings ratios ϕ_0^+ and ϕ_0^- for the positive and negative earnings surprises, respectively. That is, the model boils down to the extended Freeman-Tse (1992) model we estimated before.

The estimation results of this model are presented in Table 4. The estimation procedure is similar to the one we followed while estimating the extended Freeman-Tse (1992) model without uncertainty. The only difference is that we use only those firm-quarter observation for which at least two different analysts submitted their forecasts. This leads to a further reduction of the sample size, in particular, for the first two sub-periods, but still leaves us with a substantial number of observations for the statistical analysis.

Table 4: **Freeman-Tse (1992) extended model with uncertainty**

Coeff.	1989-1991	1992-1993	1994-1995	1996-1997
μ	-0.0006 (0.0005)	0.0005 (0.0005)	-0.0009^{*} (0.0005)	-0.0006 (0.0005)
β^{+}	0.0041^{**} (0.0011)	0.006^{**} (0.0015)	0.013^{**} (0.002)	0.011^{**} (0.0024)
δ^{+}	-0.014^{**} (0.005)	-0.0038^{**} (0.0011)	-0.01^{**} (0.0019)	-0.058^{**} (0.016)
β^{-}	0.0069^{**} (0.0012)	0.011^{**} (0.0017)	0.012^{**} (0.0027)	0.018^{**} (0.004)
δ^{-}	-0.001 (0.001)	-0.028^{**} (0.011)	-0.013^{**} (0.0025)	-0.055^{**} (0.018)
ϕ_0^{+}	2.33^{**} (0.63)	2.69^{**} (0.64)	1.31^{**} (0.23)	1.35^{**} (0.28)
ϕ_1^{+}	-2.55^{*} (1.39)	-6.17^{*} (3.79)	-6.54^{**} (1.54)	-1.51^{**} (0.41)
ϕ_0^{-}	1.13^{**} (0.2)	0.98^{**} (0.14)	1.1^{**} (0.25)	0.74^{**} (0.16)
ϕ_1^{-}	-1.34^{**} (0.63)	-1.32^{**} (0.41)	-2.95^{*} (1.56)	-0.29^{**} (0.07)
γ^{+}	2238.12^{**} (592.7)	598.1^{**} (154.5)	699.7^{**} (128.8)	1203.6^{**} (212.3)
γ^{-}	613.97^{**} (215.3)	1224.6^{**} (364.1)	643.6^{**} (168.9)	475.9^{**} (144.3)
No "Friday effect"	0.036	<0.01	<0.01	<0.01
Constant "Friday effect"	0.019	<0.01	<0.01	<0.01
Adj. R^2	0.036	0.044	0.049	0.038
No.obs	15697	15226	20670	24896

$^{*(**)}$ denotes 10(5)% significance

White heteroskedasticity-consistent standard errors in parentheses

p-values of no "Friday effect" and constant "Friday effect"

hypotheses tests are reported under the "No "Friday effect"" and

"Constant "Friday effect"" headings, respectively

Table 4 *(continued)*: **Freeman-Tse (1992) extended model with uncertainty**

Coeff.	1998-1999	2000-2001	2002-2003	2004-2006
μ	-0.003^{**} (0.0006)	0.0039^{**} (0.0007)	-0.0056^{*} (0.0006)	-0.0043 (0.0005)
β^{+}	0.01^{**} (0.002)	0.012^{**} (0.003)	0.025^{**} (0.0038)	0.016^{**} (0.0019)
δ^{+}	-0.011^{**} (0.0026)	-0.016^{**} (0.006)	-0.051 (0.036)	-0.013^{**} (0.0034)
β^{-}	0.023^{**} (0.006)	0.058^{**} (0.019)	0.022^{**} (0.006)	0.021^{**} (0.004)
δ^{-}	-0.044^{**} (0.023)	-0.086 (0.052)	-0.032^{**} (0.012)	-0.053^{**} (0.013)
ϕ_0^{+}	1.63^{**} (0.35)	1.35^{**} (0.34)	0.61^{**} (0.09)	1.02^{**} (0.12)
ϕ_1^{+}	-8.57^{**} (2.39)	-5.89^{**} (2.18)	-2.23^{**} (1.1)	-1.93^{**} (0.62)
ϕ_0^{-}	0.59^{**} (0.14)	0.23^{**} (0.06)	0.59^{**} (0.15)	0.56^{**} (0.095)
ϕ_1^{-}	-0.17^{**} (0.06)	-0.03^{**} (0.008)	-2.88^{*} (1.63)	-0.094^{**} (0.02)
γ^{+}	1340.7^{**} (226.5)	1075.9^{**} (222.1)	954.4^{**} (174.5)	935.4^{**} (116.9)
γ^{-}	290.7^{**} (100.3)	81.7^{**} (40.8)	505.3^{**} (211.3)	609.1^{**} (146.6)
No "Friday effect"	<0.01	<0.01	<0.01	<0.01
Constant "Friday effect"	<0.01	<0.01	0.023	<0.01
Adj. R^2	0.032	0.023	0.039	0.059
No.obs	25241	20670	19497	31424

$^{*(**)}$ denotes 10(5)% significance

White heteroskedasticity-consistent standard errors in parentheses

p-values of no "Friday effect" and constant "Friday effect"

hypotheses tests are reported under "No "Friday effect"" and

"Constant "Friday effect"" headings, respectively

Our estimation results strongly suggest that the pre-announcement uncertainty plays an important role in the earnings-returns relation. Moreover, we find strong evidence that the pre-announcement uncertainty affects not only the sensitivity of stock prices to the earnings surprises ("absolute" sensitivity), but also the magnitude of the "Friday effect", that is, the *relative* sensitivity of stock prices to the Friday announcements compared to those released during other trading days.

We begin with the analysis of the link between the pre-announcement uncertainty and the "absolute" sensitivity of stock returns to the earnings innovations, measured by δ^+ and δ^-. Our findings suggest that there exists a negative relationship between the level of the pre-announcement uncertainty and the strength of the earnings-return association with the estimates of both δ^+ and δ^- being significantly negative. This negative relation is also economically significant. For instance, let us consider the estimates for the years 2004-2006 to gain some impression on the role of the pre-announcement uncertainty during the last sub-period. For positive earnings surprises the marginal impact of an increase in the earnings innovation on the expected excess return with no pre-announcement uncertainty is 1.14 times larger compared to the one with forecast dispersion of 0.15 (95% quantile). The impact of the pre-announcement uncertainty is even more pronounced for the negative earnings innovation, where the stock returns appear to be 1.61 times more sensitive to the earnings surprises with no pre-announcement uncertainty compared to the earnings announcements with high level of the forecasts' dispersion.

Next, we turn to the impact of the pre-announcement uncertainty on the "Friday effect" in the earnings response function, which is measured by the parameters ϕ_1^+ and ϕ_1^- for the positive and negative earnings surprises, respectively. For a given level of the pre-announcement uncertainty the earnings response ratios are given by $\frac{1}{\phi_0^+ + \phi_1^+ UNC}$ and $\frac{1}{\phi_0^- + \phi_1^- UNC}$ for the "good" and "bad" news, respectively. Our results indicate that by the end of the 1980-s and the beginning of the 1990-s there was a pronounced "Friday effect" for both "good" and "bad" earnings announcements. More specifically, our findings suggest that during the above mentioned period stock prices were substantially less sensitive to the news released on Fridays compared to the earnings announcements released during the non-Friday trading sessions. Moreover, our results suggest that for this period the magnitude of the "Friday effect" was inversely related to the level of the pre-announcement uncertainty, proxied by the analysts' forecast dispersion. This effect is especially pronounced for the 1989-1991 period. For instance, for the earnings announcement with no analysts' forecast dispersion the estimated earnings response ratios are 0.43 and 0.88 for the positive and negative earnings surprises, respectively. That is, at the beginning of our sample period the stock prices of the firms with high quality of information disclosure were about twice more sensitive to the "good" news released during the non-Friday trading days. Similarly, for the "bad" earnings announcements not accompanied by pre-announcement uncertainty the estimated earnings-returns link is 12% stronger for the news released during the non-Friday trading days. The magnitude of the "Friday effect" also seems to decline over time.

However, the magnitude of "Friday effect" seems to be drastically declining as we move to the earnings announcements with a high levels of pre-announcement uncertainty, with the estimates of ϕ_1^+ and ϕ_1^- being significantly negative for all the sub-periods examined in our study. For instance, for the same 1989-1991 period the earnings response ratios for the earnings announcement with forecast dispersion of 0.15 are 0.52 and 1.07 for the positive and negative earnings surprises, respectively. A comparison of the earnings response ratios for the positive and negative earnings surprises provides us with a further insight into the evolution of the "Friday effect" over time. Note that for the positive unexpected earnings for all but one sub-period the estimates of ϕ_0^+ are greater that one. This finding suggests that over the last two decades the stock prices of the firms with a high quality of information disclosure were less sensitive to the "good" news released on Friday, compared to those released during the rest of the week. At the same time, for these stocks the impact of the pre-announcement uncertainty on the magnitude of the "Friday effect" is both statistically and economically significant. A different picture unfolds when we examine the earnings response ratios for the negative earnings surprises. Note that starting from the year 1996 the estimates of ϕ_0^- turned out to be smaller than one. At the same time there was a substantial decline in the magnitude of the estimates of ϕ_1^- which, though remaining statistically significant, lost their economical significance, with the 2002-2003 sub-period being the only exception. This finding supports our hypothesis that, as the level of the pre-announcement uncertainty increases, the relative sensitivity of stock prices to non-Friday earnings announcements tends to disappear. In other words, the magnitude of the "Friday effect" appears to be strongly related to the quality of the information disclosure.

6.6 Summary and Conclusions

In this paper we study the evolution of "Friday effect" over time. We focus on two equally important questions:

- Was the strategy of reporting "bad" news on Friday persistent over time?
- If so, did the investors learn about this strategy and how was it reflected in the earnings-returns relation?

Our results strongly suggest that the firms continued to report "bad" news on Fridays during the last two decades. The mean earnings surprise is significantly lower and the proportion of "bad" earnings announcements is significantly higher for the Friday earnings announcements compared to other trading days. This tendency persists over the whole time span of our study.

On the other hand, we also find strong evidence of a structural shift in the earnings-response relation. More specifically, we find a reversal in the "Friday effect" in the earnings-returns relation with stock prices becoming eventually *more* sensitive to Friday earnings announcements. Interestingly, the reversal appears to be substantially more pronounced when "bad" news is released. Further analysis indicates that the magnitude of the "Friday effect" is inversely related to the level of the pre-announcement uncertainty proxied by the analysts' forecast dispersion.

Overall, our findings suggest that over time investors learned about the tendency of the firms to release "bad" news on Fridays. The association between stock returns and earnings innovations released on Fridays became stronger over time. Moreover, our findings suggest that for the last ten years the investors systematically overreact to the "bad" earnings announcements released on Fridays, compared to their response to the "bad" news released during other trading days. A potential explanation of this finding is that investors, who learned about the firms' strategy to report "bad" news on Fridays, consider negative earnings announcements released on Fridays as particularly important ones which firms are attempting to "hide". This may lead to a closer association between the negative earnings surprises released on Fridays and the stock returns compared to the rest of the week.

Our findings suggest a number of important implications. First, our results shed an additional light on stock market efficiency, by showing how the stock market participants gather all available information to form their expectations. Second, our findings are of particular interest to firms and, in particular, to their earnings announcement policies. The results of our study suggest that the benefits from reporting "bad" news on Fridays disappeared over time. Moreover, our results suggest that since stock prices became more sensitive to Friday announcements, the strategy of reporting "bad" news on Friday misses its target. In light of our findings shifting the announcement of "bad" news from Friday to other trading days seems to be a reasonable step to follow.

Finally, we suggest a number of possible directions for further research. One of the possible extensions of this research would be to study the evolution of the "Friday effect" controlling for investors' sophistication, which could be proxied by, for instance, the share of institutional holdings. It is likely that investors' sophistication is an important factor affecting the magnitude of the "Friday effect" and the dynamics and the speed of investors' learning about this effect. It would also be interesting to conduct a similar study for stock markets other than the US, to study how the difference in trading regulations and the information disclosure policies affect the magnitude and the evolution of a "Friday effect" over time.

Chapter 7

Samenvatting (Summary in Dutch)

Gedurende de recente decennia was er sprake van een snelle convergentie van de nationale economieën naar een globale markt. De serieuze financiële crises waarvan we in het laatstse decennium getuige zijn geweest, benadrukken het belang van het beter begrijpen van de verbanden tussen de nationale economieën alsmede de noodzaak om de gevolgen van de globalisatie voor de verbreiding van financiële crises over de wereld beter te begrijpen. Echter, er bestaan nog diverse gaten in de literatuur over de gevolgen van de globalisatie op het gemeenschappelijk bewegen van de internationale aandelenmarkten. Het eerste deel van dit proefschrift bestudeert de dynamiek van de overdracht over grenzen heen van prijsinformatie tussen internationale aandelenmarkten.

Onze analyse laat zien dat de aandelenmarkten significant meer zijn geïntergreerd gedurende de laatste twee-en-een-halve decennia. We vinden eveneens sterk bewijs van “contagion”, het negatief beïnvloed worden van de ene economie door de koersen van financiële activa op de financiële markten van een andere economie. Dit "contagion effect" lijkt asymmetrisch, veel significanter voor negatieve prijsschokken, en lijkt gerelateerd aan de aandelenmarktvolatiliteit en economische condities. Deze bevindingen benadrukken een belangrijke rol van deze factoren in de internationale verbreiding van aandelenmarktcrises. De economische kosten van het negeren van contagion of het asymmetrische karakter ervan zijn ook significant. Door het benadrukken van het belang om rekening te houden met de veranderingen in de afhankelijkheidsstructuur tussen de financiële activa hebben deze resultaten tevens belangwekkende implicaties voor strategieën om portefeuilles te beheren.

Vervolgens richten we onze aandacht op het informatie-overdrachts-mechanisme tussen waardepapieren waarvan de koersen zowel op de beurs van New York als die van Tokio staan genoteerd. Deze twee aandelenbeurzen zijn de twee grootste en meest invloedrijke beurzen ter wereld. Zulke waardepapieren, die op verschillende beurzen worden verhandeld, terwijl ze eenzelfde fundamentele waarde representeren, vormen een unieke gelegenheid om de informatie-overdracht tussen markten te begrijpen. Met name helpen zulke waardepapieren om het prijsonthullingsproces te begrijpen in een wereld waarin financiële systemen meer en meer geïntegreerd raken.

We vinden duidelijk empirisch bewijs van informatie-asymmetrie waarbij de beurs van Tokio domineert in termen van informatie, aangezien het leeuwendeel van het prijsonthullingsproces daar plaats vindt. Het duurt langer voordat prijsschokken op de markt van Tokio zich hebben verspreid op de markt in de VS dan omgekeerd, een bevinding die lijkt te suggereren dat het gedrag van de VS-helft van de waardepapieren-tweeling kan worden voorspeld op basis van de informatie die beschikbaar komt tijdens de handelsuren in Tokio. Dit impliceert dat er mogelijkheden zouden kunnen bestaan om winstgevende grensoverschrijdende strategieën te ontwikkelen. Daarnaast lijkt de prijsonthulling te zijn gerelateerd aan het niveau van de handelsactiviteiten, die we benaderen met behulp van het handelsvolume. Dit resultaat ondersteunt andere studies, zoals Blume, Easley en O'Hara (1994), die suggereren dat het handelsvolume extra informatie verschaft bovenop de informatie al impliciet aanwezig in de aandelenprijzen.

In het tweede deel van het proefschrift wordt de aandacht gericht op markstefficiëntie, met name hoe snel de informatie wordt opgenomen in de aandelenprijzen. Het belang om het mechanisme te begrijpen hoe nieuws wordt gereflecteerd in prijzen van waardepapieren kan nauwelijks worden overschat. Het is essentieel voor investeringsbeslissingen in de financieringspraktijk, voor het beleid van het management van bedrijven hoe bedrijfsnieuws naar buiten te brengen, alsmede voor beleidsmakers van wie de beslissingen vaak een grote impact hebben op het functioneren van de aandelenmarkten.

We beginnen met het bestuderen van de dynamische relatie tussen aandelenrendementen, handelsvolume en volatiliteit. We toetsen diverse theoretische modellen die deze variabelen in verband brengen met de dynamiek van de aandelenrendementen op basis van een steekproef van zowel koersen van geaggregeerde aandelenindices als koersen van individuele aandelen. We vinden dat de omvang van de aandelenrendementen-omkeringen en "momentum" (verdergaan volgens een trend) voornamelijk gerelateerd is met de aandelenmarktvolatiliteit en niet het handelsvolume, zoals gesuggereerd is door voorgaande studies. Echter, het handelsvolume lijkt een belangrijke rol te spelen in het prijsonthullingsproces alsmede in het gelijk op bewegen van aandelenkoersen, een bevinding die het belang laat zien van de informatie die bevat is in het handelsvolume. Deze bevindingen verschaffen ook een alternatieve verklaring voor de "hoge volume premie", zoals gedocumenteerd door Gervais *et al.* (2001).

Vervolgens onderzoeken we het verband tussen voorschriften hoe bedrijfsinformatie naar buiten te brengen en marktefficiëntie. We bestuderen de implicaties van de Sarbanes-Oxley Wet −beoogd om een antwoord te geven op een reeks zware bedrijfsschandalen− voor de marktefficiëntie en de nauwkeurigheid waarmee analisten bedrijfsinkomsten kunnen voorspellen. We onderzoeken of de wetgeving van stringentere voorschriften over hoe bedrijfsinformatie naar buiten te brengen het vertrouwen van investeerders en beursanalisten heeft hersteld, een vertrouwen dat behoorlijk was geschaad door de talloze gevallen van bedrijfsfraude gedurende de periode 2001-2002.

We vinden als resultaat dat na de invoering van de Sarbanes-Oxley wetgeving er een substantiële toename gemeten kan worden in de coëfficiënten die de snelheid van informatie-aanpassing meten. Deze bevinding lijkt te suggereren dat als gevolg van de wetgeving de aandelenmarkten in de VS vanuit het oogpunt van informatie efficiënter geworden zijn. Maar we vinden ook overtuigend empirisch bewijs dat de beursanalisten meer bovenmatig pessimistisch geworden zijn in termen van hun voorspellingen van de bedrijfsinkomsten. We interpreteren deze bevinding als bewijs dat de analisten voorzichtiger geworden zijn in het interpreteren van informatie vrijgegeven door het management van bedrijven. Over het geheel genomen laten deze bevindingen een sterk verband zien tussen de kwaliteit van informatieverschaffing en het efficiënt functioneren van de aandelenmarkten.

Het laatste hoofdstuk van het proefschrift gaat over het strategisch kiezen van het moment waarop informatie bekend wordt gemaakt en de reactie van de aandelenkoersen op die informatie. We bestuderen de veronderstelde tendens van bedrijven om "slecht" nieuws tegen het weekeinde bekend te maken, met name op vrijdagen, zo gebruikmakend van de verslapte aandacht van investeerders vanwege het naderende weekeinde. We vinden dat gedurende de laatste twee decennia bedrijven consequent meer "slecht" nieuws op vrijdagen naar buiten hebben gebracht dan op andere weekdagen. We constateren ook dat de gevoeligheid van aandelenrendementen op vrijdag-aankondigingen, vergeleken met andere weekdagen, langzaam maar zeker is toegenomen, een toename die met name uitgesproken lijkt te zijn als er sprake is van "slecht" nieuws. Bovendien vinden we een sterk verband tussen het "vrijdageffect" en het niveau van de onzekerheid voorafgaand aan een nieuwsaankondiging. Deze bevindingen suggereren dat de tendens van bedrijven om ongunstige aankondigingen op vrijdagen te doen inderdaad gerelateerd is aan de verslappende aandacht van investeerders vanwege het naderende weekeinde, maar ook dat de voordelen van deze strategie in de loop der tijd minder is geworden, een resultaat met belangwekkende implicaties voor het beleid van bedrijven inzake nieuwsaankondigingen.

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